Notebook requirements.txt

# Installing and loading all required libraries

```
! pip install verstack
```

```
!pip install ta
```

```
!pip install seglearn
```

```
!pip install yfinance
```

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import seglearn
import yfinance as yf
import warnings
warnings.filterwarnings("ignore")
from statsmodels.graphics.tsaplots import _prepare_data_corr_plot, _plot_corr
import statsmodels.graphics.utils as utils
from statsmodels.tsa.stattools import pacf
```

# Loading the daily data

```
# Connecting to the google drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.r
```

```
#loading daily data
daily_data = pd.read_csv('/content/drive/MyDrive/MADS_23_DL_final_project/data/crypto_data
```

```
# columns in our data
daily_data.columns
```

```
Index(['Open Time', 'Open', 'High', 'Low', 'Close', 'Volume', 'train_test',
       'Crypto'],
      dtype='object')
```

```
#first 5 rows of our data
daily_data.head()
```

| | Open Time | Open | High | Low | Close | Volume | train_test | Crypto |
|---|---|---|---|---|---|---|---|---|
| 0 | 2013-04-01 | 93.155 | 105.90 | 93.155 | 104.750 | 11008.524 | Train | BTC |
| 1 | 2013-04-02 | 104.720 | 127.00 | 99.000 | 123.016 | 24187.398 | Train | BTC |
| 2 | 2013-04-03 | 123.001 | 146.88 | 101.511 | 125.500 | 31681.780 | Train | BTC |
| 3 | 2013-04-04 | 125.500 | 143.00 | 125.500 | 135.632 | 15035.206 | Train | BTC |
| 4 | 2013-04-05 | 136.000 | 145.00 | 135.119 | 142.990 | 11697.741 | Train | BTC |

```
daily_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20746 entries, 0 to 20745
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Open Time   20746 non-null  object
 1   Open        20746 non-null  float64
 2   High        20746 non-null  float64
 3   Low         20746 non-null  float64
 4   Close       20746 non-null  float64
 5   Volume      20746 non-null  float64
 6   train_test  20746 non-null  object
 7   Crypto      20746 non-null  object
dtypes: float64(5), object(3)
memory usage: 1.3+ MB
```

# EDA

```
#setting Open Time as index
daily_data=daily_data.set_index('Open Time')
```

```
# train test split to make sure that there's no contamination
train_df = daily_data[daily_data['train_test']=='Train']
test_df = daily_data[daily_data['train_test']=='Test']
```

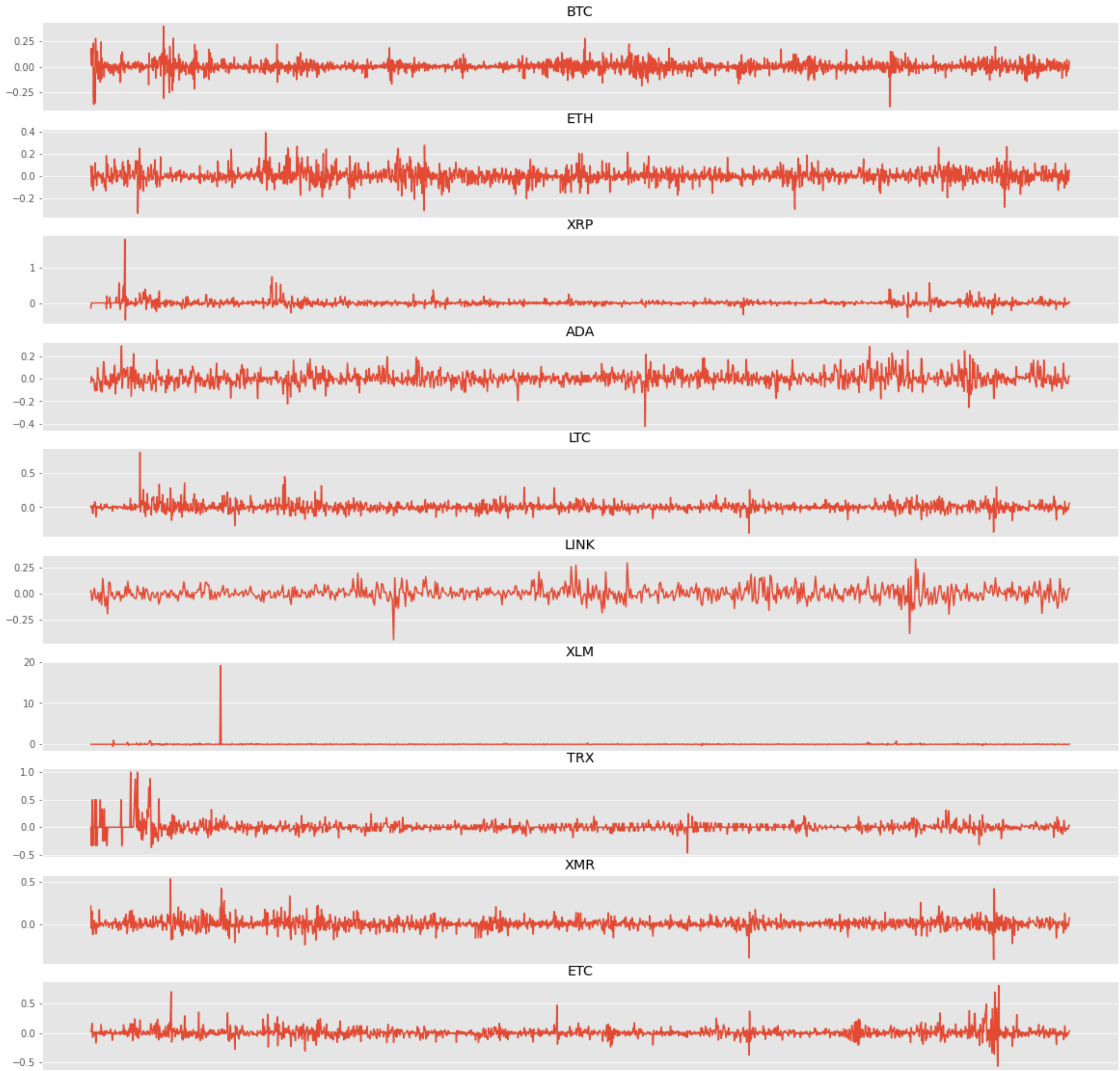
```
#function to create daily returns column
def calculate_pct_change(df):
  coins = df.Crypto.unique()
  df_pct_change = pd.DataFrame()
  for coin in coins:
    x = df[df['Crypto']==coin]
    x['pct_change_1day'] = x['Close'].pct_change(1)
    df_pct_change = pd.concat([df_pct_change,x])
  return df_pct_change
```

```
#Adding daily returns to test and train data
train_df= calculate_pct_change(train_df)
test_df= calculate_pct_change(test_df)
```

```
train_df.head()
```

| Open Time | Open | High | Low | Close | Volume | train_test | Crypto | pct_change_1da |
|---|---|---|---|---|---|---|---|---|
| 2013-04-01 | 93.155 | 105.90 | 93.155 | 104.750 | 11008.524 | Train | BTC | Na |
| 2013-04-02 | 104.720 | 127.00 | 99.000 | 123.016 | 24187.398 | Train | BTC | 0.17437 |
| 2013-04-03 | 123.001 | 146.88 | 101.511 | 125.500 | 31681.780 | Train | BTC | 0.02019 |

```
#Plotting 1 day returns for all coins

coins = train_df['Crypto'].unique()

f,ax = plt.subplots(len(coins),figsize=(20,20))
for i in range(len(coins)):

  ax[i].plot(train_df.index[train_df['Crypto']==coins[i]],train_df.pct_change_1day[train_d
  ax[i].title.set_text(coins[i])
  ax[i].set_xticks([])
```




Daily return is generally considered stationary. Here, the mean Return for all coins seems to be constant, but we can't say the same for volatility. But we are going ahead with the stationary assumption anyways and plotting pacf for all coins to find out relevant lags that we can use to model our dep variable; 1 day Return

```
# pacf plot function

def plot_pacf_drop(x, ax=None, lags=None, alpha=.05, method='ywunbiased',
              use_vlines=True, title='Partial Autocorrelation', zero=True,
              vlines_kwargs=None, drop_no=0, **kwargs):

    lags_orig=lags
    fig, ax = utils.create_mpl_ax(ax)
    vlines_kwargs = {} if vlines_kwargs is None else vlines_kwargs
    lags, nlags, irregular = _prepare_data_corr_plot(x, lags, zero)
    confint = None
    if alpha is None:
        acf_x = pacf(x, nlags=nlags, alpha=alpha, method=method)
```

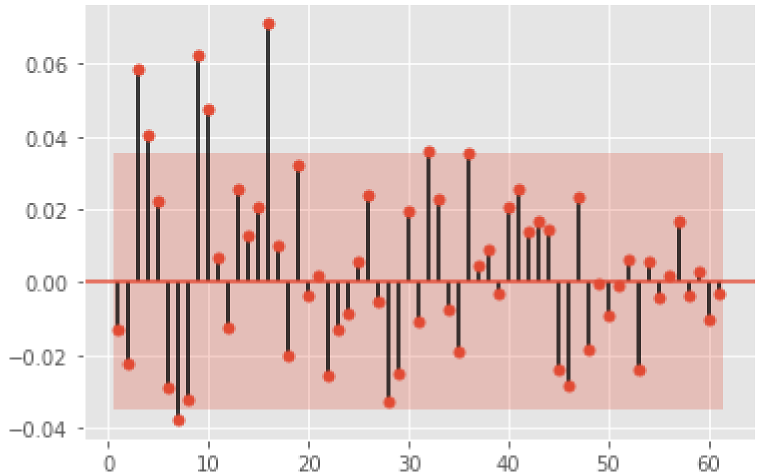
```
    else:
        acf_x, confint = pacf(x, nlags=nlags, alpha=alpha, method=method)

    if drop_no:
        acf_x = acf_x[drop_no+1:]
        confint = confint[drop_no+1:]
        lags, nlags, irregular = _prepare_data_corr_plot(x, lags_orig-drop_no, zero)

    _plot_corr(ax, title, acf_x, confint, lags, False, use_vlines,
               vlines_kwargs, **kwargs)

    return fig
```

We will be collecting all the relevant lags (lags with abs(pacf) >0.06) for all the individual coins in a list and will be using all of these lags in our model

```
#list to collect all relevant lags
master_list=[]

coins = train_df['Crypto'].unique()
for coin in coins:
  #pacf plot for all coins
  plt.figure()
  plot_pacf_drop(train_df['pct_change_1day'][train_df['Crypto']==coin].dropna(),lags=62,dr
  k=pacf(train_df.pct_change_1day[train_df['Crypto']==coin].dropna(), nlags=62, alpha=0.05
  ar_name=str(coin)+"array"
  ar_name=[]
  for i in range(1,len(k[0])):
    if k[0][i]>=0.06 or k[0][i]<=-0.06:
      ar_name.append(i)
      master_list.append(i)

  print(f"Significant lags for {coin} is {ar_name}")

print(f"Significant lags we'll be taking for daily returns {set(master_list)}")
plt.show()

#master list with all unique relevant lags
lag_list=list(set(master_list))
```

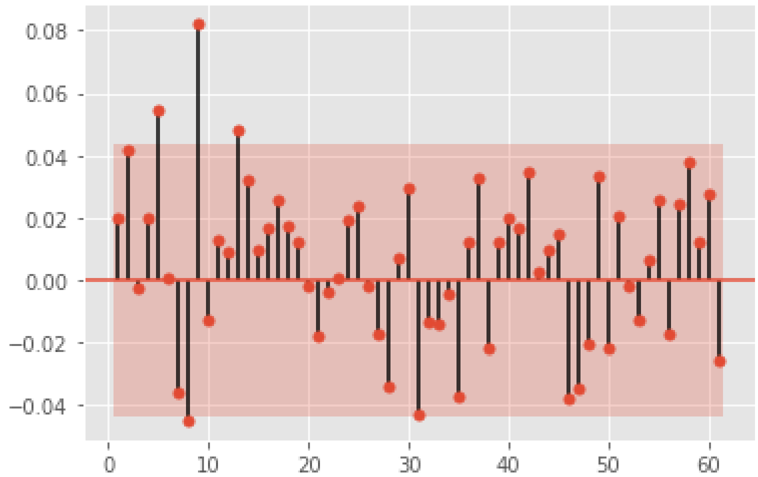
```
Significant lags for BTC is [10, 17]
Significant lags for ETH is [10]
Significant lags for XRP is [2, 3, 16, 35, 36, 60]
Significant lags for ADA is [1, 2, 4, 35, 36, 59]
Significant lags for LTC is [6]
Significant lags for LINK is [1, 4, 12, 13, 20, 29, 39, 48, 49]
Significant lags for XLM is []
Significant lags for TRX is [2, 3, 9, 11, 15, 17, 20, 22, 38, 45, 52]
Significant lags for XMR is [1, 6, 23]
Significant lags for ETC is [1, 4, 6, 9, 14, 20, 39, 54, 59]
Significant lags we'll be taking for daily returns {1, 2, 3, 4, 6, 9, 10, 11, 12, 13,
<Figure size 432x288 with 0 Axes>
```

BTC



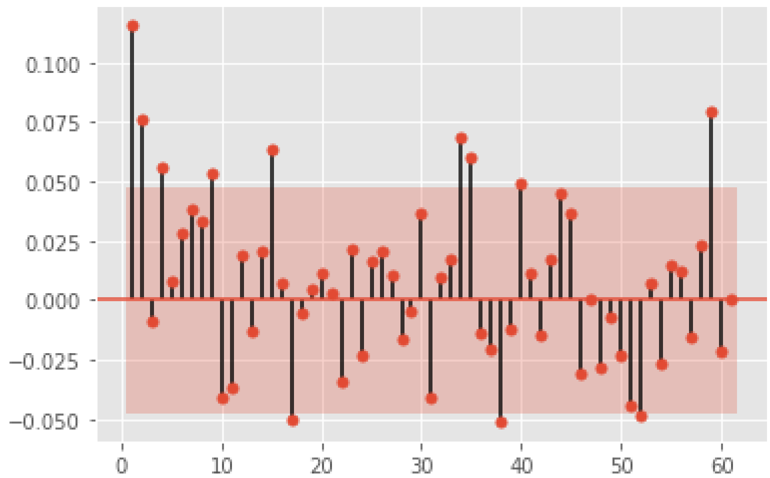

```
<Figure size 432x288 with 0 Axes>
```

ETH

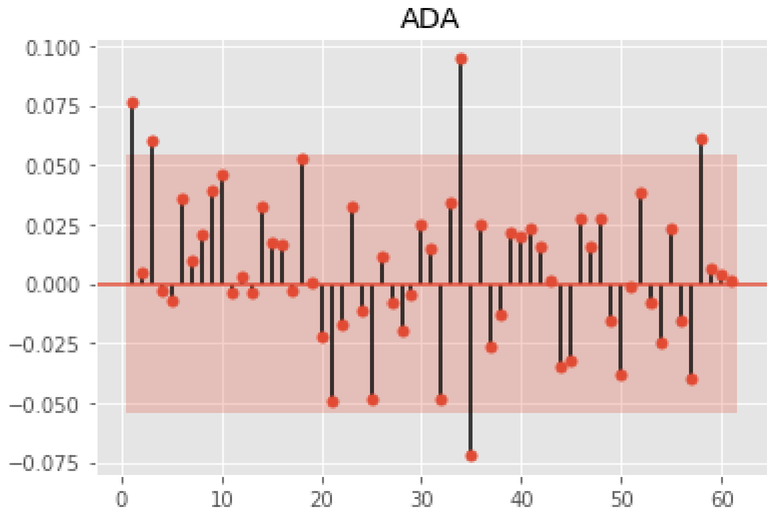



```
<Figure size 432x288 with 0 Axes>
```

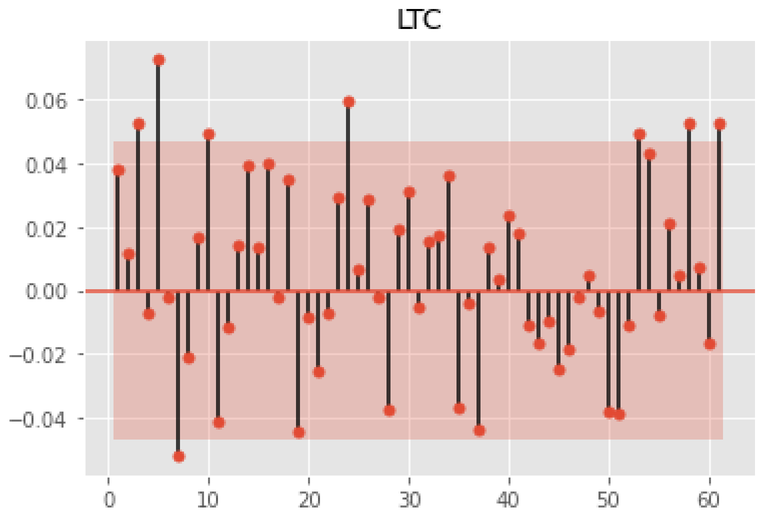
XRP



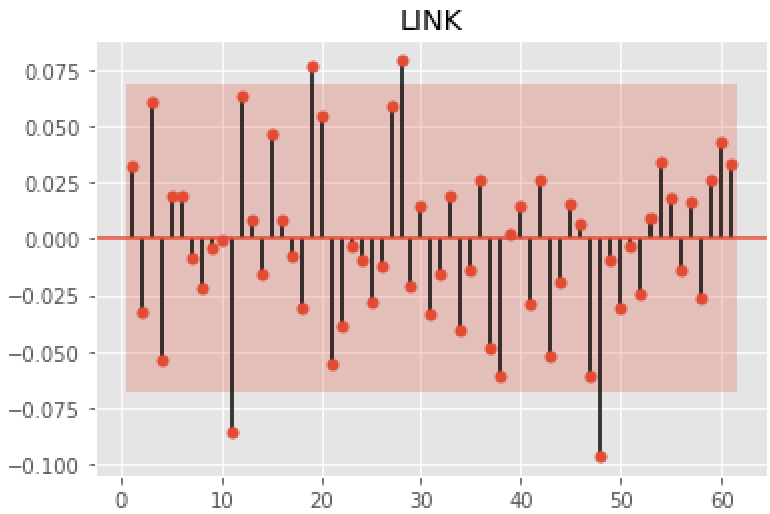
<Figure size 432x288 with 0 Axes>



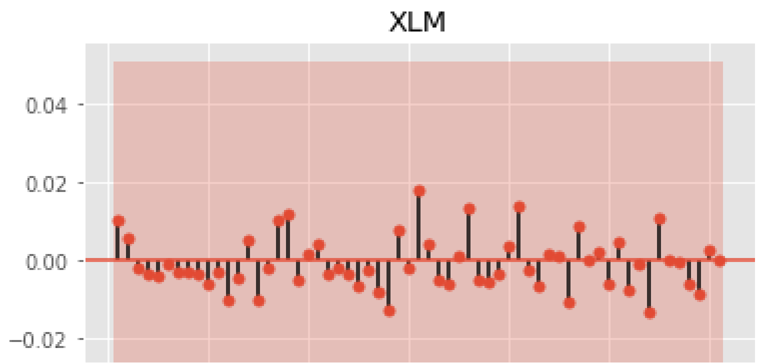

<Figure size 432x288 with 0 Axes>

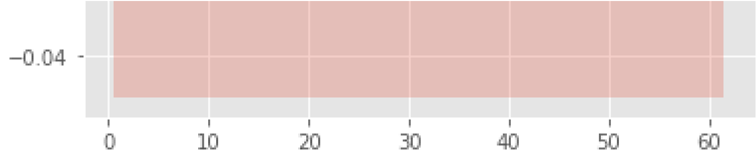



<Figure size 432x288 with 0 Axes>

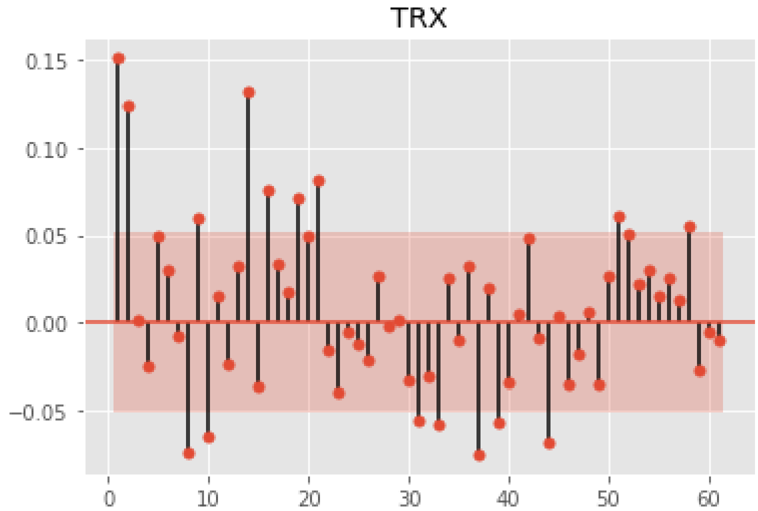



<Figure size 432x288 with 0 Axes>

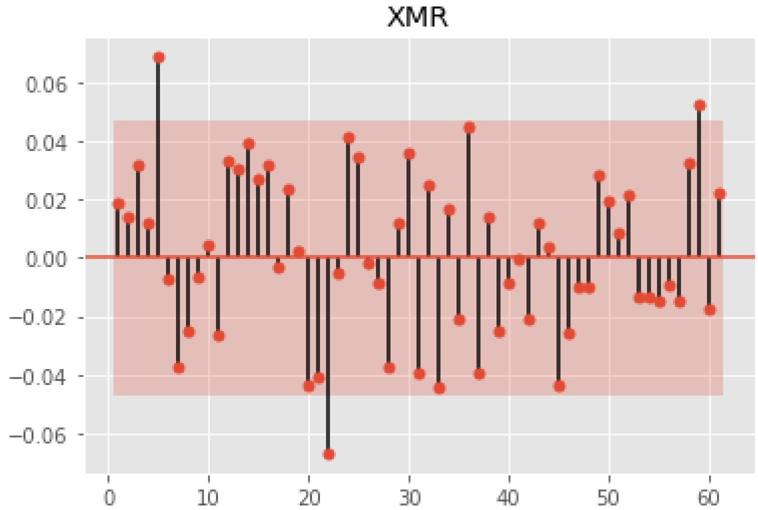




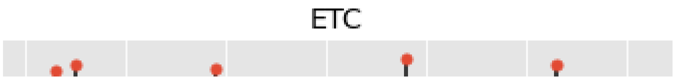

```
<Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
```




## Feature Engineering

### 1.Adding lagged Technical Indicators as features


Technical indicators use price and volume information to identify statistical trends from historical trading activity to predict future movements in price or volume.We will model technical indicators for all the crypto coins seperately from daily data. For that we will be using the Technical Analysis library in python.

We will be using four classes of Technical Indicators namely, Momentum, Volume, Volatility and Trend. We will be modelling all the TI's for the four classes mentioned above. Further information about individual TI's could be found here: [TI summary]

1. Momentum Indicators (18 TI's):

```
'momentum_rsi', 'momentum_stoch_rsi',
'momentum_stoch_rsi_k', 'momentum_stoch_rsi_d', 'momentum_tsi',
'momentum_uo', 'momentum_stoch', 'momentum_stoch_signal', 'momentum_wr',
'momentum_ao', 'momentum_roc', 'momentum_ppo', 'momentum_ppo_signal',
'momentum_ppo_hist', 'momentum_pvo', 'momentum_pvo_signal',
'momentum_pvo_hist', 'momentum_kama'
```

2. Volume Indicators (13 TI's):

```
'volume_adi', 'volume_obv', 'volume_cmf',
'volume_fi', 'volume_em', 'volume_sma_em', 'volume_vpt', 'volume_vwap',
'volume_mfi', 'volume_nvi', 'volatility_bbm', 'volatility_bbh',
'volatility_bbl'
```

3. Volatility Indicators (21 TI's):

```
'volatility_bbm', 'volatility_bbh',
'volatility_bbl', 'volatility_bbw', 'volatility_bbp', 'volatility_bbhi',
'volatility_bbli', 'volatility_kcc', 'volatility_kch', 'volatility_kcl',
'volatility_kcw', 'volatility_kcp', 'volatility_kchi',
'volatility_kcli', 'volatility_dcl', 'volatility_dch', 'volatility_dcm',
'volatility_dcw', 'volatility_dcp', 'volatility_atr', 'volatility_ui'
```

4. Trend Indicators (34 TI's):

```
'trend_macd', 'trend_macd_signal', 'trend_macd_diff', 'trend_sma_fast',
'trend_sma_slow', 'trend_ema_fast', 'trend_ema_slow',
'trend_vortex_ind_pos', 'trend_vortex_ind_neg', 'trend_vortex_ind_diff',
'trend_trix', 'trend_mass_index', 'trend_dpo', 'trend_kst',
'trend_kst_sig', 'trend_kst_diff', 'trend_ichimoku_conv',
'trend_ichimoku_base', 'trend_ichimoku_a', 'trend_ichimoku_b',
'trend_stc', 'trend_adx', 'trend_adx_pos', 'trend_adx_neg', 'trend_cci',
'trend_visual_ichimoku_a', 'trend_visual_ichimoku_b', 'trend_aroon_up',
'trend_aroon_down', 'trend_aroon_ind', 'trend_psar_up',
'trend_psar_down', 'trend_psar_up_indicator',
'trend_psar_down_indicator'
```

```
#Function to add all TI indicators and shifting them by 1 time step
def add_TI_indicators(df):
  master_df_list=[]
  from ta import add_all_ta_features
  coins = df['Crypto'].unique()
  for coin in coins:
    df_name = add_all_ta_features(df[df['Crypto']==coin], open="Open", high="High", low="L
    for ti in df_name.columns[8:]:
      df_name[ti] = df_name[ti].shift(1)
    master_df_list.append(df_name)

  #final data with all the new TI features shifted by 1 time step
  return pd.concat(master_df_list)
```

```
#Adding all TI indicators and shifting them by 1 time step
train_df=add_TI_indicators(train_df)
test_df=add_TI_indicators(test_df)
```

```
train_df.head()
```

| | Open | High | Low | Close | Volume | train_test | Crypto | pct_change_1da |
|---|---|---|---|---|---|---|---|---|
| **Open Time** | | | | | | | | |
| **2013-04-01** | 93.155 | 105.90 | 93.155 | 104.750 | 11008.524 | Train | BTC | Na |
| **2013-04-02** | 104.720 | 127.00 | 99.000 | 123.016 | 24187.398 | Train | BTC | 0.17437 |
| **2013-04-03** | 123.001 | 146.88 | 101.511 | 125.500 | 31681.780 | Train | BTC | 0.02019 |
| **2013-04-04** | 125.500 | 143.00 | 125.500 | 135.632 | 15035.206 | Train | BTC | 0.08073 |
| **2013-04-05** | 136.000 | 145.00 | 135.119 | 142.990 | 11697.741 | Train | BTC | 0.05425 |

5 rows × 94 columns

## 2.Adding lagged pct_change_1day as features for every relevant lag in the lag list

```
#function to create lagged pct_change col for every relevant lag
def create_shift_features(df,col,lag_list):
  master_df_list=[]
  crypto_coins = df['Crypto'].unique()
  for coin in crypto_coins:
    temp_df = df[df['Crypto']==coin]
    for lag in lag_list:

      temp_df['{}d_lag_{}'.format(lag,col)] = temp_df[col].shift(periods=lag)
    master_df_list.append(temp_df)
  return pd.concat(master_df_list)
```

```
#adding all lags to trai and test data
train_df = create_shift_features(train_df,'pct_change_1day',lag_list)
test_df = create_shift_features(test_df,'pct_change_1day',lag_list)
#Adding lagged Close value to plot the predictions for Close at the end
test_df=create_shift_features(test_df,'Close',[1])
```

```
test_df.head()
```

| | Open | High | Low | Close | Volume | train_test | Crypto | pct_chang |
|---|---|---|---|---|---|---|---|---|
| **Open Time** | | | | | | | | |
| **2021-10-01** | 43828.89 | 48500.00 | 43287.44 | 48165.76 | 38375.517 | Test | BTC | |
| **2021-10-02** | 48185.61 | 48361.83 | 47438.00 | 47657.69 | 12310.011 | Test | BTC | -0. |
| **2021-10-03** | 47649.00 | 49300.00 | 47119.87 | 48233.99 | 14411.104 | Test | BTC | 0. |
| **2021-10-04** | 48233.99 | 49530.53 | 46895.80 | 49245.54 | 25695.213 | Test | BTC | 0. |
| **2021-10-05** | 49244.13 | 51922.00 | 49057.18 | 51493.99 | 30764.491 | Test | BTC | 0. |

5 rows × 124 columns

## 3.Adding Time based features as ordinals

```
def encode_cyclicals(df_x):
    #"year","month","day","dayofweek"


    df_x['year'] = pd.DatetimeIndex(df_x.index).year
```

```
    df_x['month'] = pd.DatetimeIndex(df_x.index).month
    df_x['day'] = pd.DatetimeIndex(df_x.index).day
    df_x['weekday'] = pd.DatetimeIndex(df_x.index).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)


    return df_x
```

```
#adding time based features
train_df = encode_cyclicals(train_df)
test_df = encode_cyclicals(test_df)
```

## 4.One hot Encoding the coins

```
# One hot encoding the train data and dropping all the NA
y_dummies = pd.get_dummies(train_df['Crypto'], prefix='Crypto', drop_first= False)
train_df = pd.concat([train_df, y_dummies], axis=1)
train_df=train_df.dropna()
```

```
# One hot encoding the test data
y_dummies = pd.get_dummies(test_df['Crypto'], prefix='Crypto', drop_first= False)
test_df = pd.concat([test_df, y_dummies], axis=1)
test_df=test_df.dropna()
```

```
train_df.head()
```

| | Open | High | Low | Close | Volume | train_test | Crypto | pct_change_1day |
|---|---|---|---|---|---|---|---|---|
| **Open Time** | | | | | | | | |
| **2013-06-01** | 127.370 | 129.00 | 127.00 | 128.79 | 2656.044 | Train | BTC | 0.005308 |
| **2013-06-02** | 128.190 | 132.65 | 117.00 | 120.46 | 30651.941 | Train | BTC | -0.064679 |

```
len(train_df)
```

```
16515
```

06-04

```
len(test_df)
```

```
3011
```

We have 16515 rows to train our model and 3011 for testing

## Modelling our Target variable

```
# train test split for target col
train_target = train_df.pct_change_1day

test_target=test_df.pct_change_1day

#For plotting the results at the end not for training
train_crypto_col=train_df.Crypto
test_crypto_col=test_df.Crypto
test_Close=test_df.Close
test_Close_1dlag=test_df["1d_lag_Close"]

#dropping all the redundant columns
train_df.drop(['others_dr', 'others_dlr', 'others_cr','train_test','pct_change_1day','Open
test_df.drop(['others_dr', 'others_dlr', 'others_cr','train_test','pct_change_1day','Open'
```

```
len(train_df)
```

```
16515
```

```
len(test_df)
```

```
3011
```

```
len(train_df.columns)
```

```
129
```

```
len(test_df.columns)
```

```
129
```

We will be using 129 columns for training our Regressor

## Baseline model

```
from sklearn.dummy import DummyRegressor

#loading the mean dummy regressor as the baseline model
dummy_model = DummyRegressor(strategy="mean")

#fitting the dumb model
dummy_model.fit(train_df,train_target)
```

```
DummyRegressor()
```

```
from sklearn.metrics import mean_squared_error
from math import sqrt

#predicting t+1
test_pred_dummy = dummy_model.predict(test_df)

#calculating RMSE
rms = sqrt(mean_squared_error(test_target, test_pred_dummy))
print("Root mean squared error on test:",rms)
```

```
Root mean squared error on test: 0.04872778321537305
```

```
#creating the dataframe for plotting the predictions v/s true values
test_plot_df_dummy=test_target.to_frame()
test_plot_df_dummy["test_pred"]=test_pred_dummy
test_plot_df_dummy["Crypto"]=test_crypto_col
```

```
#plotting the predictions vs true values for all coins
coins = test_plot_df_dummy['Crypto'].unique()
f,ax = plt.subplots(len(coins),figsize=(20, 25))

for i in range(len(coins)):
  label_1="True Returns "+str(coins[i])
  label_2="Predicted Returns "+str(coins[i])
  ax[i].plot(test_plot_df_dummy.index[test_plot_df_dummy['Crypto']==coins[i]],test_plot_df
  ax[i].plot(test_plot_df_dummy.index[test_plot_df_dummy['Crypto']==coins[i]],test_plot_df
  ax[i].title.set_text(coins[i])
  ax[i].set_xticks([])
  ax[i].legend()
```


BTC
True Returns BTC
Predicted Returns BTC
ETH
True Returns ETH
Predicted Returns ETH
XRP
True Returns XRP
Predicted Returns XRP
ADA
True Returns ADA
Predicted Returns ADA
LTC
True Returns LTC
Predicted Returns LTC
LINK
True Returns LINK
Predicted Returns LINK
XLM
True Returns XLM
Predicted Returns XLM
TRX
True Returns TRX
Predicted Returns TRX
XMR
True Returns XMR
Predicted Returns XMR
ETC
True Returns ETC
Predicted Returns ETC

# LGBM Regression

## LGBM Feature Set Selection Using Random Selection Method

```
#function to select feature set based on random numbers
def select_feature_space(df,selector):
  #selector=[volume ta, volatility ta, trent ta, momentum ta,7 day lag,31 day PCA lags,62

  master_df_list=[]
  for i in range(len(selector)):
    if i==0 and selector[i]==1:
      master_df_list.append(df[df.columns[:10]])
    elif i==1 and selector[i]==1:
      master_df_list.append(df[df.columns[10:31]])
    elif i==2 and selector[i]==1:
      master_df_list.append(df[df.columns[31:65]])
    elif i==3 and selector[i]==1:
      master_df_list.append(df[df.columns[65:83]])
    elif i==4 and selector[i]==1:
      master_df_list.append(df[df.columns[83:88]])
    elif i==5 and selector[i]==1:
      master_df_list.append(df[df.columns[88:101]])
    elif i==6 and selector[i]==1:
      master_df_list.append(df[df.columns[101:112]])
    elif i==7 and selector[i]==1:
      master_df_list.append(df[df.columns[112:119]])


  master_df_list.append(df[df.columns[119:]])
  return pd.concat(master_df_list,axis=1)
```

```
import random
from sklearn.metrics import mean_squared_error
```

```
from math import sqrt
import lightgbm as lgb

#Choose number of iterations
iterations=100

master_list=[]
#creating empty df to collect the results


# defining parameters for lgbm
params = {
    'task': 'train',
    'boosting': 'gbdt',
    'objective': 'regression',
    'max_depth':12,
    'num_leaves': 4096,
    'learning_rate': 0.05,
    'metric': {'l2','l1'},
    'verbose': -1,
    'n_estimators':250
}

for i in range(iterations):

  #switch to randomly select the feature space
  selector=random.choices([1,0],k=8)
  #for the corner case
  if selector==[0,0,0,0,0,0,0,0]:
    continue

  print(f"The Random Selector List is {selector}")

  #selector=[volume ta, volatility ta, trent ta, momentum ta,7day PCA lags,7-31 day PCA la

  #creating train and test data
  train_df_final=select_feature_space(train_df,selector)
  test_df_final=select_feature_space(test_df,selector)

  # loading data
  lgb_train = lgb.Dataset(train_df_final, train_target)
  lgb_eval = lgb.Dataset(test_df_final,test_target, reference=lgb_train)

  # fitting the model
  lgb_model_trial = lgb.train(params,
               train_set=lgb_train,
               valid_sets=lgb_eval,
               early_stopping_rounds=30)
  # prediction
  test_pred_lgbm_trial = lgb_model_trial.predict(test_df_final)


  #calculating rmse
  rms_trial = sqrt(mean_squared_error(test_target, test_pred_lgbm_trial))
```

```
    selector.append(rms_trial)
    master_list.append(selector)

#dataframe to store the results of our randomisation feature selection process
df_rmse = pd.DataFrame(master_list,columns=["volume_ta", "volatility_ta", "trent_ta", "mom
```

```
#results sorted from best to worst rmse
df_rmse.sort_values(by=['rmse'])
```

| | volume_ta | volatility_ta | trent_ta | momentum_ta | 7_day_PCAlags | 8-31_day_PCAlags |
|---|---|---|---|---|---|---|
| **93** | 0 | 1 | 0 | 0 | 1 | 0 |
| **45** | 0 | 1 | 0 | 1 | 1 | 0 |
| **50** | 0 | 1 | 0 | 1 | 1 | 0 |
| **91** | 1 | 0 | 1 | 1 | 0 | 1 |
| **74** | 0 | 0 | 1 | 1 | 0 | 1 |
| **...** | ... | ... | ... | ... | ... | ... |
| **41** | 0 | 1 | 0 | 0 | 0 | 1 |
| **79** | 1 | 1 | 0 | 0 | 0 | 1 |
| **20** | 1 | 1 | 1 | 0 | 0 | 1 |
| **73** | 1 | 1 | 1 | 0 | 0 | 1 |
| **6** | 1 | 0 | 0 | 0 | 0 | 0 |

```
#creating the final test and train data based on the best rmse score
selector_list=list(df_rmse.loc[df_rmse.sort_values(by=['rmse']).index[0]][:7])
train_df_final_v1=select_feature_space(train_df,selector_list)
test_df_final_v1=select_feature_space(test_df,selector_list)
```

```
len(train_df_final_v1.columns)
```

```
36
```

For our final train data, we only have 36 columns. Lagged Volatility Indicators and lagged pct values for a week seems to be the relevant features

```
#The columns we use for training
train_df_final_v1.columns
```

```
Index(['volatility_bbm', 'volatility_bbh', 'volatility_bbl', 'volatility_bbw',
       'volatility_bbp', 'volatility_bbhi', 'volatility_bbli',
       'volatility_kcc', 'volatility_kch', 'volatility_kcl', 'volatility_kcw',
```

```
            'volatility_kcp', 'volatility_kchi', 'volatility_kcli',
            'volatility_dcl', 'volatility_dch', 'volatility_dcm', 'volatility_dcw',
            'volatility_dcp', 'volatility_atr', 'volatility_ui',
            '1d_lag_pct_change_1day', '2d_lag_pct_change_1day',
            '3d_lag_pct_change_1day', '4d_lag_pct_change_1day',
            '6d_lag_pct_change_1day', 'Crypto_ADA', 'Crypto_BTC', 'Crypto_ETC',
            'Crypto_ETH', 'Crypto_LINK', 'Crypto_LTC', 'Crypto_TRX', 'Crypto_XLM',
            'Crypto_XMR', 'Crypto_XRP'],
           dtype='object')
```

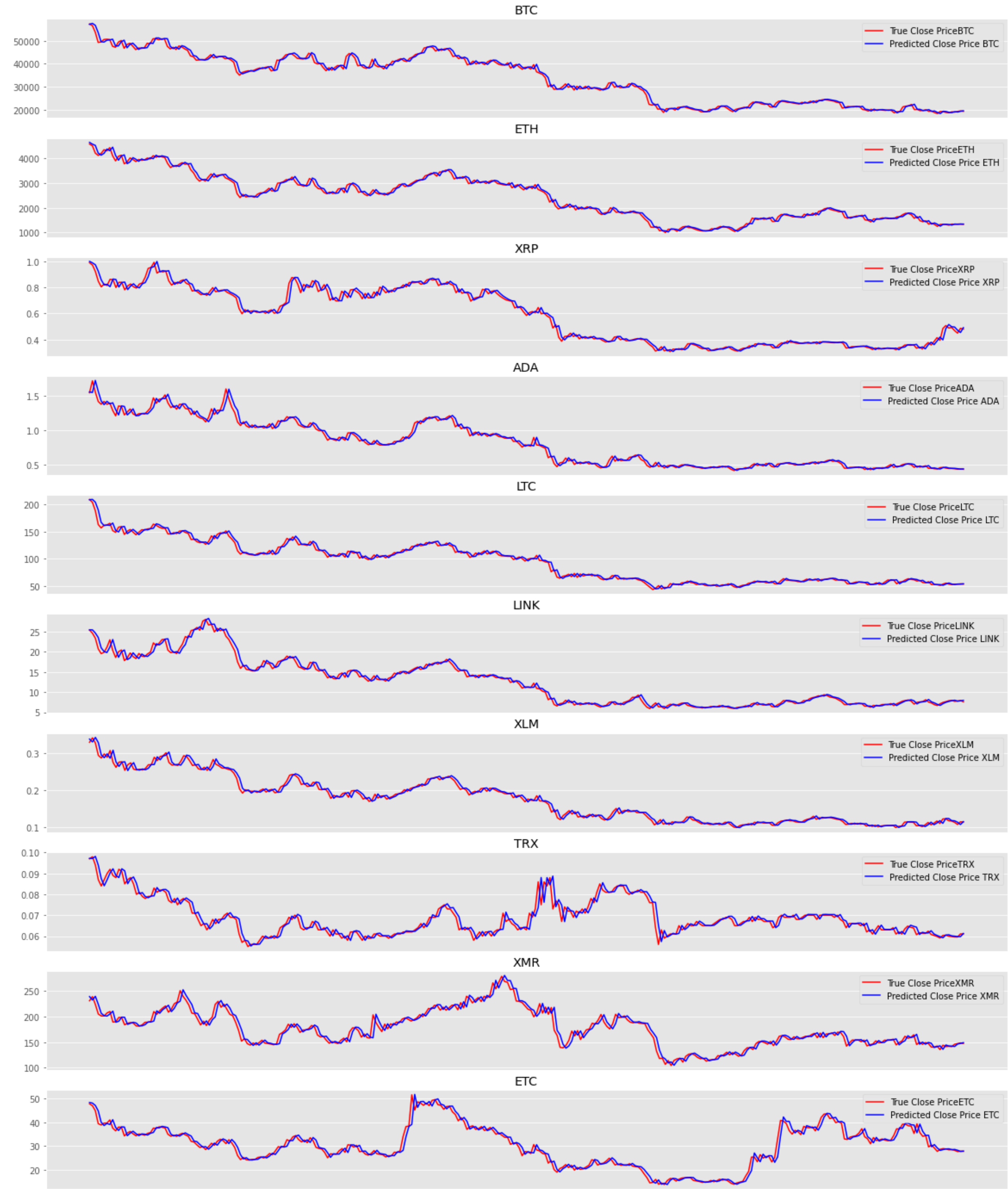
```
#Using our best performing features for our LGBM Model
import lightgbm as lgb

# defining parameters
params = {
    'task': 'train',
    'boosting': 'gbdt',
    'objective': 'regression',
    'max_depth':12,
    'num_leaves': 4096,
    'learning_rate': 0.05,
    'metric': {'l2','l1'},
    'verbose': -1,
    'n_estimators':250
}


# loading data
lgb_train = lgb.Dataset(train_df_final_v1, train_target)
lgb_eval = lgb.Dataset(test_df_final_v1,test_target, reference=lgb_train)


# fitting the model
lgb_model = lgb.train(params,
                 train_set=lgb_train,
                 valid_sets=lgb_eval,
                 early_stopping_rounds=100)



# prediction
test_pred_lgbm = lgb_model.predict(test_df_final_v1)

from sklearn.metrics import mean_squared_error
from math import sqrt
#calculating rmse
rms = sqrt(mean_squared_error(test_target, test_pred_lgbm))
print("Root mean squared error on test for LGBM model:",rms)
```

```
Root mean squared error on test for LGBM model: 0.048215272624038276
```

```
#creating the dataframe for plotting the predictions v/s true values
test_plot_df_lgbm=test_target.to_frame()
test_plot_df_lgbm["test_pred"]=test_pred_lgbm
test_plot_df_lgbm["test_pred"]=test_pred_lgbm
test_plot_df_lgbm["Crypto"]=test_crypto_col
```

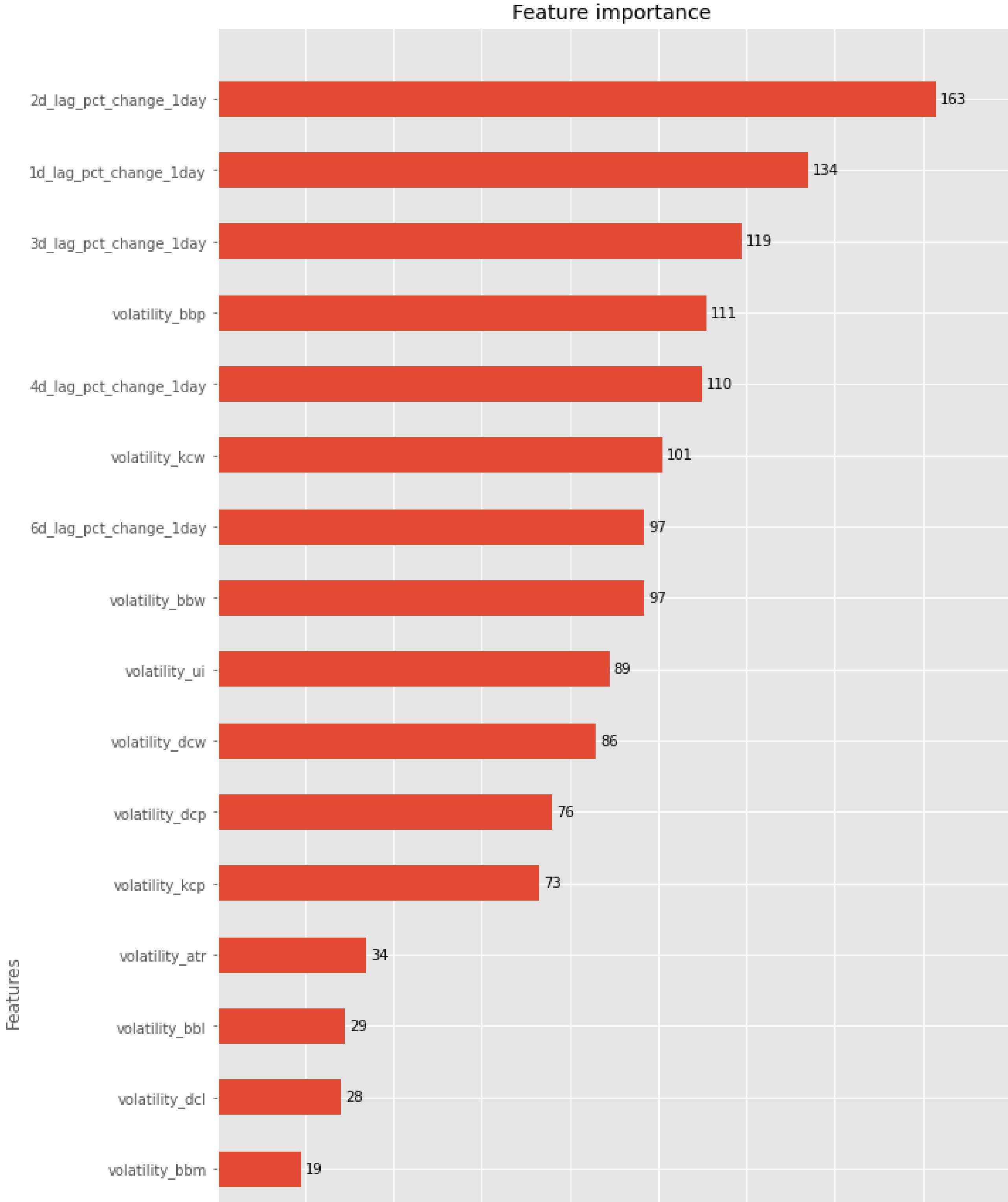
```
test_plot_df_lgbm["Close_1dlag"]=test_Close_1dlag
#calculating the next day Close price using the predicted returns
test_plot_df_lgbm["Close_pred"]=test_plot_df_lgbm["Close_1dlag"]*test_plot_df_lgbm["test_p
test_plot_df_lgbm["Close"]=test_Close

#plotting the predictions vs true values for all coins
coins = test_plot_df_lgbm['Crypto'].unique()
f,ax = plt.subplots(len(coins),figsize=(20, 25))

for i in range(len(coins)):
  label_1="True Returns "+str(coins[i])
  label_2="Predicted Returns "+str(coins[i])
  ax[i].plot(test_plot_df_lgbm.index[test_plot_df_lgbm['Crypto']==coins[i]],test_plot_df_l
  ax[i].plot(test_plot_df_lgbm.index[test_plot_df_lgbm['Crypto']==coins[i]],test_plot_df_l
  ax[i].title.set_text(coins[i])
  ax[i].set_xticks([])
  ax[i].legend()
```


```
#Using the 1 day return predictions to calculate t+1 closing price and plotting vs true va
coins = test_plot_df_lgbm['Crypto'].unique()
f,ax = plt.subplots(len(coins),figsize=(20, 25))

for i in range(len(coins)):
  label_1="True Close Price"+str(coins[i])
  label_2="Predicted Close Price "+str(coins[i])
  ax[i].plot(test_plot_df_lgbm.index[test_plot_df_lgbm['Crypto']==coins[i]],test_plot_df_l
  ax[i].plot(test_plot_df_lgbm.index[test_plot_df_lgbm['Crypto']==coins[i]],test_plot_df_l
  ax[i].title.set_text(coins[i])
  ax[i].set_xticks([])
  ax[i].legend()
```


BTC
True Close PriceBTC
Predicted Close Price BTC
ETH
True Close PriceETH
Predicted Close Price ETH
XRP
True Close PriceXRP
Predicted Close Price XRP
ADA
True Close PriceADA
Predicted Close Price ADA
LTC
True Close PriceLTC
Predicted Close Price LTC
LINK
True Close PriceLINK
Predicted Close Price LINK
XLM
True Close PriceXLM
Predicted Close Price XLM
TRX
True Close PriceTRX
Predicted Close Price TRX
XMR
True Close PriceXMR
Predicted Close Price XMR
ETC
True Close PriceETC
Predicted Close Price ETC

```
# plotting feature importance
lgb.plot_importance(lgb_model, height=.5,figsize=(10,25))
```

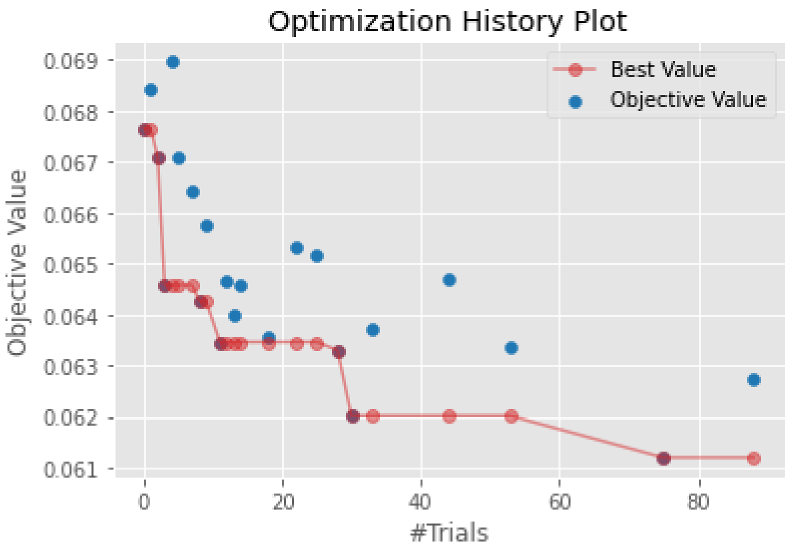
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fec720bac90>
```

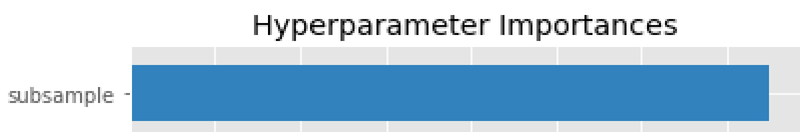


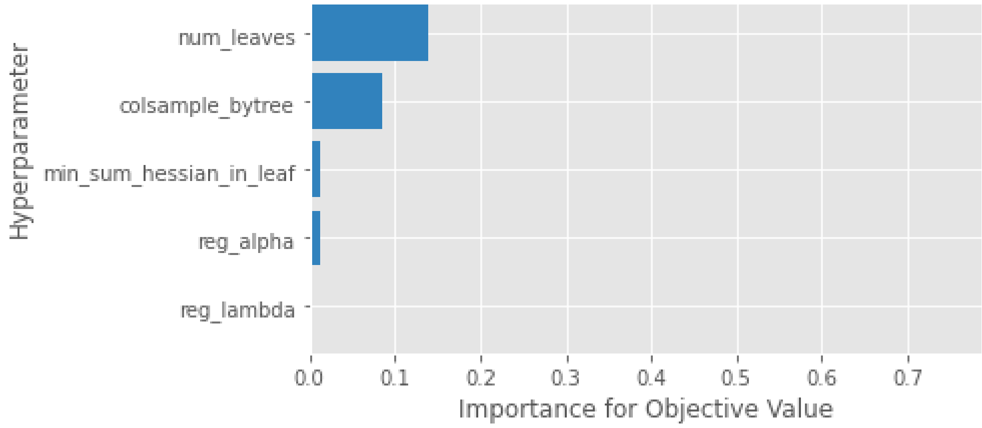

```
#Hyper Parameter Tuning LGBM
from verstack import LGBMTuner
tuned_lgbm = LGBMTuner(metric = 'rmse')
tuned_lgbm.fit(train_df_final_v1, train_target)
```

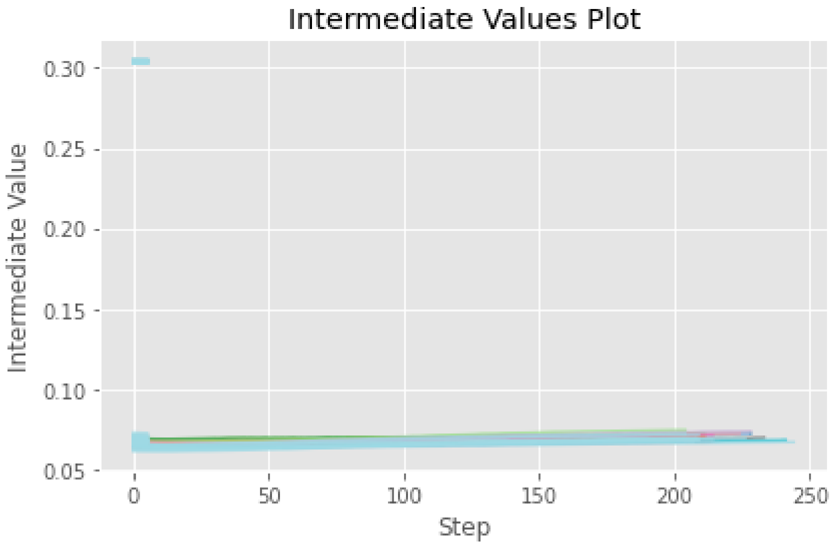
```
* Initiating LGBMTuner.fit
    . Settings:
    .. Trying 100 trials
    .. Evaluation metric: rmse
    .. Study direction: minimize rmse

    . Trial number: 0 finished
    .. Optimization score (lower-better): rmse: 0.06765917156304006
...........................................................................
    . Trial number: 1 finished
    .. Optimization score (lower-better): rmse: 0.06844006569107612
...........................................................................
    . Trial number: 2 finished
    .. Optimization score (lower-better): rmse: 0.06709567069918762
...........................................................................
    . Trial number: 3 finished
    .. Optimization score (lower-better): rmse: 0.06457561684747148
...........................................................................
    . Trial number: 4 finished
    .. Optimization score (lower-better): rmse: 0.06896574331152938
...........................................................................
    . Trial number: 5 finished
    .. Optimization score (lower-better): rmse: 0.06710747471273541
...........................................................................
    . Trial number: 7 finished
    .. Optimization score (lower-better): rmse: 0.0664334023268232
...........................................................................
    . Trial number: 8 finished
    .. Optimization score (lower-better): rmse: 0.0642560913508916
...........................................................................
    . Trial number: 9 finished
    .. Optimization score (lower-better): rmse: 0.06574795421402513
...........................................................................
    . Trial number: 11 finished
    .. Optimization score (lower-better): rmse: 0.06345588400777555
...........................................................................
    . Trial number: 12 finished
    .. Optimization score (lower-better): rmse: 0.06465648688629537
...........................................................................
    . Trial number: 13 finished
    .. Optimization score (lower-better): rmse: 0.06397095973103285
...........................................................................
    . Trial number: 14 finished
    .. Optimization score (lower-better): rmse: 0.0645613562364028
...........................................................................
    . Trial number: 18 finished
    .. Optimization score (lower-better): rmse: 0.06356854662172572
...........................................................................
    . Trial number: 22 finished
    .. Optimization score (lower-better): rmse: 0.06531391442689093
...........................................................................
    . Trial number: 25 finished
    .. Optimization score (lower-better): rmse: 0.06515188495839837
...........................................................................
    . Trial number: 28 finished
    .. Optimization score (lower-better): rmse: 0.06329647986702953
...........................................................................
    . Trial number: 30 finished
    .. Optimization score (lower-better): rmse: 0.062011598055484195
```

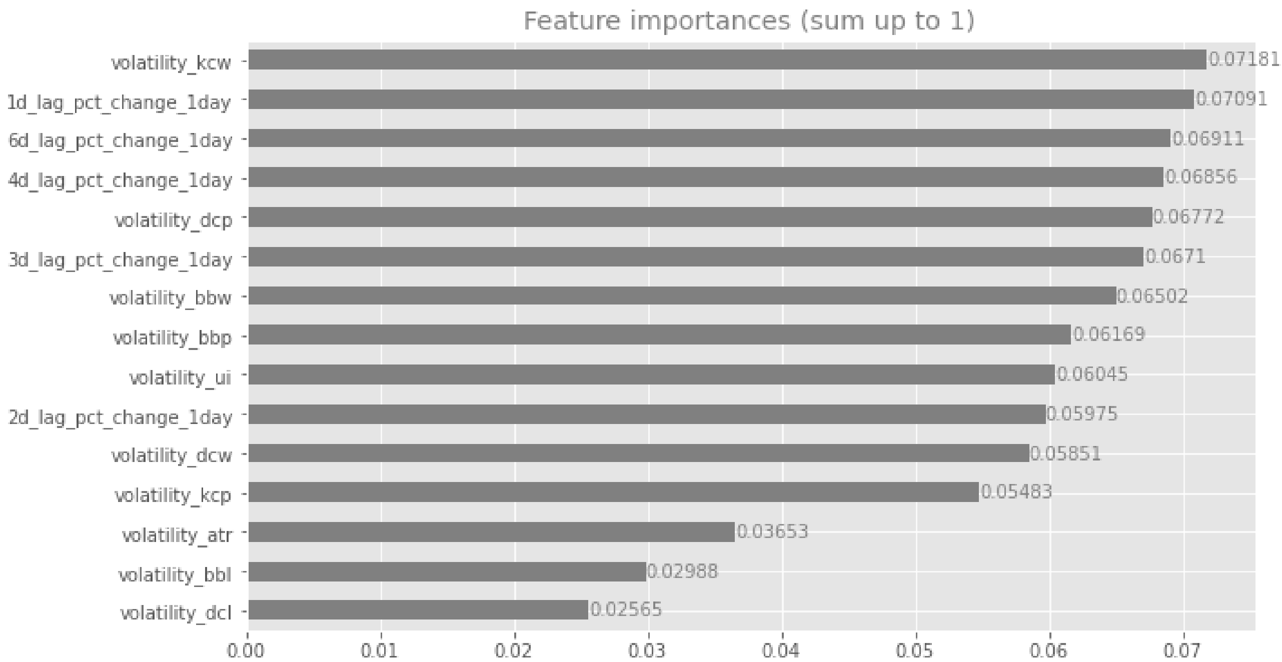
```
............................................................................
    . Trial number: 33 finished
    .. Optimization score (lower-better): rmse: 0.06370496517586999
............................................................................
    . Trial number: 44 finished
    .. Optimization score (lower-better): rmse: 0.06470679093036116
............................................................................
    . Trial number: 53 finished
    .. Optimization score (lower-better): rmse: 0.06337669305077161
............................................................................
    . Trial number: 75 finished
    .. Optimization score (lower-better): rmse: 0.06120100918241552
............................................................................
    . Trial number: 88 finished
    .. Optimization score (lower-better): rmse: 0.06273893682697483
............................................................................

   - Tune n_estimators with early_stopping
Training until validation scores don't improve for 200 rounds
[100]	train's lgb_rmse: 0.0648147	valid's lgb_rmse: 0.303638
[200]	train's lgb_rmse: 0.0632601	valid's lgb_rmse: 0.303567
[300]	train's lgb_rmse: 0.0621083	valid's lgb_rmse: 0.303605
[400]	train's lgb_rmse: 0.0612466	valid's lgb_rmse: 0.303646
Early stopping, best iteration is:
[217]	train's lgb_rmse: 0.0630557	valid's lgb_rmse: 0.30356

   - Fitting optimized model with the follwing params:
learning_rate                    : 0.02
num_leaves                       : 224
colsample_bytree                 : 0.5821743201769795
subsample                        : 0.9812669409975833
verbosity                        : -1
random_state                     : 42
objective                        : regression
metric                           : rmse
num_threads                      : 0
reg_alpha                        : 2.767273165671379
min_sum_hessian_in_leaf          : 0.9534939063057168
reg_lambda                       : 1.7454215440714303e-05
n_estimators                     : 217
```






```
. Optuna hyperparameters optimization finished
.. Best trial number:75    |     rmse:          0.06120100918241552
```

```
# prediction using tuned lgbm model

from sklearn.metrics import mean_squared_error
from math import sqrt


test_pred = tuned_lgbm.predict(test_df_final_v1)
```

```
rms = sqrt(mean_squared_error(test_target, test_pred))
print("Root mean squared error on test:",rms)
```

```
Root mean squared error on test: 0.04850202285455725
```

Our tuned LGBM using Vestack is performing worse than our untuned LGBM model

## XG Boost Regression

```
import xgboost as xgb

#creating train and test matrix for xgb
dmatrix_train = xgb.DMatrix(data=train_df_final_v1,label=train_target)
dmatrix_test = xgb.DMatrix(data=test_df_final_v1,label=test_target)


#setting the params for xgb
params = {'objective': 'reg:linear', 'eval_metric': 'rmse', 'n_estimators':25}

evallist = [(dmatrix_test, 'eval'), (dmatrix_train, 'train')]

num_round = 10
#training xg model
xg_reg = xgb.train(params,dmatrix_train,num_round)
```

```
[16:15:29] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
```

```
# prediction
test_pred_xg = xg_reg.predict(dmatrix_test)
#calculating rmse
rms = sqrt(mean_squared_error(test_target, test_pred_xg))
print("Root mean squared error on test for XGBOOST:",rms)
```

```
Root mean squared error on test for XGBOOST: 0.052040710210716636
```

## Random Forest

```
from sklearn.ensemble import RandomForestRegressor

#setting params for rf
N_ESTIMATORS = 25
RANDOM_STATE = 452543634
#loading the rf model
RF_base_model = RandomForestRegressor(n_estimators=N_ESTIMATORS,random_state=RANDOM_STATE)
#fitting the model
RF_base_model.fit(train_df_final_v1,train_target)
```

```
RandomForestRegressor(n_estimators=25, random_state=452543634)
```

```
# prediction
test_pred_rf = RF_base_model.predict(test_df_final_v1)
#calculating rmse
rms = sqrt(mean_squared_error(test_target, test_pred_rf))
print("Root mean squared error on test for Random Forest:",rms)
```

```
Root mean squared error on test for Random Forest: 0.05097493461057416
```

## Elastic Net Regression

```
#Hyper Parameter Tuning the model
from sklearn.linear_model import ElasticNetCV
from sklearn.model_selection import RepeatedKFold
from sklearn.linear_model import ElasticNet
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
# define model
ratios = np.arange(0, 1, 0.01)
alphas = [1e-5, 1e-4, 1e-3, 1e-2, 1e-1, 0.0, 1.0, 10.0, 100.0]
model = ElasticNetCV(l1_ratio=ratios, alphas=alphas, cv=cv, n_jobs=-1)
# fit model
model.fit(train_df_final_v1,train_target)
# summarize chosen configuration
print('alpha: %f' % model.alpha_)
print('l1_ratio_: %f' % model.l1_ratio_)
```

```
alpha: 0.100000
l1_ratio_: 0.000000
```

```
#Using the tuned Parameters for our model
Elastic_Net_model= ElasticNet(alpha= model.alpha_, l1_ratio= model.l1_ratio_)
# fit model
Elastic_Net_model.fit(train_df_final_v1,train_target)
```

```
ElasticNet(alpha=0.1, l1_ratio=0.0)
```

```
# prediction
test_pred_en = Elastic_Net_model.predict(test_df_final_v1)
#calculte rmse
rms = sqrt(mean_squared_error(test_target, test_pred_en))
print("Root mean squared error on test for Elastic Net Regression:",rms)
```

```
Root mean squared error on test for Elastic Net Regression: 0.048523745128252235
```

### For creating the requirements file

```
from pip._internal.utils.misc import get_installed_distributions
import sys
#import numpy as np # imported to test whether numpy shows up, which it does!
```