```
# -*- coding: utf-8 -*-
Created on Sat Nov 5 11:48:04 2022
@author: Nayeem Badshah, EMP_ID: 191323
import math
import pandas_datareader as web # version should be 0.10.0
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential, load model
from keras.layers import Dense, LSTM
import matplotlib.pyplot as plt
from openpyxl import load workbook
from datetime import date, datetime
import scipy.stats
plt.style.use('fivethirtyeight')
scaler = MinMaxScaler(feature range=(0,1))
def plot_stock(df, stock name):
    plt.figure(figsize=(16,8))
    plt.title(f"Clos Price History {stock_name}")
    plt.plot(df['Close'])
    plt.xlabel('Date', fontsize=(18))
    plt.ylabel('Clos Price', fontsize=(18))
    plt.show()
def scale data(dataset):
    scaled_data = scaler.fit_transform(dataset)
    return scaled data
def filter_data(df,column):
    # create a new dataframe with only close column
    data = df.filter([column])
    return data
```

```
def train test split(scaled data, training data len, window size):
   # create the scaled training dataset
  train data = scaled data[0:training data len,:]
   # split the data into x train and y train data sets
   x train = []
   v train = []
   p n = window size
   for i in range(p n, len(train data)):
      x train.append(train data[i-p n:i,0])
      y train.append(train data[i, 0])
   # convert the x train and y train to numpy arrays
   x train, y train = np.array(x train), np.array(y train)
   # reshape the data
   x train = np.reshape(x train, (x train.shape[0], x train.shape[1], 1))
   # create the testting data set
   # a new array containing scaled values from index 1543 to 2003
  test_data = scaled_data[training_data_len - window_size: , :]
   # creat x test and y test
   x test = []
   y test = scaled data[training data len:,:]
   for i in range(window_size, len(scaled_data) - (training_data_len - window_size)):
      x test.append(test data[i-window size:i,0])
   # convert the data to numpy array
   x test = np.array(x_test)
   # reshape the data
   x test = np.reshape(x test, (x test.shape[0], x test.shape[1], 1))
   return x_train, y_train, x_test, y_test
```

```
def get training data len(df, training size):
    # get the number of rows to train the model on
   return math.ceil(len(df) * training_size)
def model build train(x train, y train, lstm input layer, lstm middle layer, dense layer, epochs):
    model = Sequential()
   model.add(LSTM(lstm_input_layer, return_sequences=True, input_shape = (x_train.shape[1],1)))
   model.add(LSTM(lstm middle layer, return sequences=False))
   model.add(Dense(dense layer))
   model.add(Dense(1))
   # compile the model
   model.compile(optimizer='adam', loss='mean squared error') # for Manik root mean squared error
   # train the model
    model.fit(x_train, y_train, batch_size=1, epochs=epochs)
    return model
def model_predict(model, x test):
    # get the model's predicted price values
    preds = model.predict(x test)
    return preds
def run model iteration(df, hyper params):
   # filter data with only close column
    data = filter data(df, 'Close')
   # scale data with Min Max Scaler
    scaled dataset = scale data(data.values)
    run data = []
   models = []
   for index, hyper_param in hyper_params.iterrows():
        trainig data size = hyper param[0]
        hyper param = hyper param[1:].astype(int)
        training data len = get training data len(data, training data size)
        # split data into train test
       x_train, y_train, x_test, y_test = \
            train test split(scaled dataset, training data len, hyper param['window size'])
```

```
# model build and train
        model = model build train(x train = x train,\)
                                  y train = y train,
                                  lstm_input_layer = hyper_param['lstm_input_layer'],
                                  lstm middle layer = hyper param['lstm middle layer'],
                                  dense layer = hyper param['dense layer'],
                                  epochs = hyper param['epochs'])
        models.append(model)
        y preds = scaler.inverse transform(model predict(model, x test))
        y test = scaler.inverse transform(y test)
        rmse = get rmse(y preds, y test)
        accuracy = get_accuracy(y_test, y_preds)
        train data, validation data = \
            consolidate train validation data(data, y preds, training data len)
        # plot_after_pred(train_data, validation_data)
        # val data = validation data.copy()
        run info = {
            'Run'
                                : index,
            'trainig data len' : trainig data size,
            'window size'
                                : hyper_param['window_size'],
            'lstm input layer' : hyper param['lstm input layer'],
            'lstm middle layer' : hyper param['lstm middle layer'],
            'dense_layer'
                                : hyper param['dense layer'],
                                : hyper param['epochs'],
            'epochs'
            'RMSE'
                                : rmse,
            'Accuracy'
                                : accuracy
        run data.append(run info)
        print(run info)
    return run data, models
def get accuracy(real, predict):
    real = np.array(real) + 1
    predict = np.array(predict) + 1
    percentage = 1 - np.sqrt(np.mean(np.square((real - predict) / real)))
    return percentage * 100
```

```
def get_rmse(y_preds, y_test):
    # get root mean squared error (RMSE)
    rmse = np.sqrt(np.mean(y preds - y test)**2)
    return rmse
def df index alter(df):
    df = df.sort values(by=['Date'],ascending=True)
    # setting the index as date
    df.index = df['Date']
   # drop date column as it is now index column
    df = df.drop(['Date'],axis=1)
    return df
def consolidate train validation data(df, preds, training data len):
    # plot the data
    train = df[:training data len].copy()
    valid = df[training data len:].copy()
    valid['Predictions'] = preds
    return train, valid
def plot after pred(train, valid, title, stock name):
    # visulize the data
    plt.figure(figsize=(16,8))
    plt.title(title)
    plt.xlabel('Date', fontsize=18)
    plt.ylabel(f'Closr Price {stock name}', fontsize=18)
    plt.plot(train['Close'])
    plt.plot(valid[['Close', 'Predictions']])
    plt.legend(['Train', 'Actual', 'Predictions'], loc='lower right')
    plt.show()
    return
def forecast(model, window size, scaled dataset, days):
    last window size = len(scaled dataset)-window size
    last winow df = scaled dataset[last window size:]
    last winow df = last winow df.reshape((1, window size, 1))
    future days = days
    future preds = []
    temp data = []
```

```
for day in range(future days):
        if day == 0:
            y hat = model.predict(last_winow_df)
            y hat = scaler.inverse transform(y hat)
           future preds.append(y_hat_[0][0])
           temp data = list(last winow df.flatten())
            temp data.append(y hat[0][0])
            temp data = temp data[1:]
        else:
            temp data = np.array(temp data).reshape((1, window size, 1))
            y hat = model.predict(temp data)
            y hat = scaler.inverse transform(y hat)
           future_preds.append(y_hat_[0][0])
            temp data = list(temp data.flatten())
            temp_data.append(y_hat[0][0])
           temp data = temp data[1:]
    return future preds
def mean confidence interval(data, confidence):
    a = 1.0 * np.array(data)
    n = len(a)
   m, se = np.mean(a), scipy.stats.sem(a)
   h = se * scipy.stats.t.ppf((1 + confidence) / 2., n-1)
    return m, m-h, m+h
def check forecast(forecasted data, upper bound, lower bound):
    forecast df = pd.DataFrame({'Forecast':forecasted data})
    forecast df['upper bound'] = upper bound
   forecast df['lower bound'] = lower bound
   forecast df['is in between'] = forecast df['Forecast'].between(forecast df['lower bound'],\
                                                                   forecast_df['upper_bound'], inclusive='both')
    return forecast df
def model evalution forecasting(model path, df path, window size, training data size, future days, stock name, ci):
    # get NASDAQ dataset
    df = pd.read excel(df path)
   # alter index to date
    df = df index alter(df)
```

```
# plot the whole data
   plot stock(df, stock name)
   model = load model(model path)
   # filter data with only close column
   data = filter data(df, 'Close')
   # scale data with Min Max Scaler
   scaled dataset = scale data(data.values)
   # get training data length
   training data len = get training data len(data, training data size)
   # split data into train test
   x train, y train, x test, y test =\
      train_test_split(scaled_dataset, training_data_len, window_size)
   t1 = scaler.inverse transform(model.predict(x test))
   train, valid = consolidate_train_validation_data(df[['Close']], t1, training_data_len)
   future close = forecast(model, window size, scaled dataset, future days)
   d = pd.DataFrame(future_close,columns=['Predictions'])
   d.index = pd.date range(date(2022, 11, 7), date(2022, 11, 16), freq='D')
   valid1 = valid.append(d)
   plot after pred(train, valid1, stock name, stock name)
   mean, lower bound, upper bound = mean confidence interval(future close,confidence=ci)
   forecast df = check forecast(future close, upper bound, lower bound)
   forecast df.index = pd.date range(date(2022, 11, 7), date(2022, 11, 16), freq='D')
   return df, train, valid, valid1, forecast df
if __name__ == "__main__":
   nifty df path = "PATH TO NIFTY DATA"
   ftse df path = "PATH TO FTSE DATA"
   nasdaq df path = "PATH TO NASDAQ DATA"
```

```
df nifty = pd.read excel(nifty df path)
df ftse = pd.read excel(ftse df path)
df_nasdaq = pd.read_excel(nasdaq_df_path)
# import hyper params
hyper params path = "PATH TO HYPER PARAMETERS DATA"
hyper_params = pd.read_excel(hyper_params_path, "hyper_params")
# train nifty data
run df nifty, models_nifty = run_model_iteration(df_nifty, hyper_params)
nifty best model idx = run df nifty[run df nifty['RMSE'] == run df nifty['RMSE'].min()]['Run'].values[0]
# save best model
models nifty[nifty best model_idx].save("SAVE_MODEL_TO_SPECIFIED_PATH")
# train FTSE data
run_df_ftse, models_ftse = run_model_iteration(df_ftse, hyper_params)
ftse best model idx = run df ftse[run df ftse['RMSE'] == run df ftse['RMSE'].min()]['Run'].values[0]
# save best model
models ftse[ftse best model idx].save("SAVE MODEL TO SPECIFIED PATH")
# train NASDAO data
run df nasdaq, models_nasdaq = run_model_iteration(df_nasdaq, hyper_params)
nasdaq best model idx = run df nasdaq[run df nasdaq['RMSE'] == run df nasdaq['RMSE'].min()]['Run'].values[0]
# save best model
models_nasdaq[nasdaq_best_model_idx].save("SAVE_MODEL_TO_SPECIFIED_PATH")
nasdag model path = "NASDAQ MODEL PATH"
df_nasdaq, train_nasdaq, valid_nasdaq, valid1_nasdaq, forecast_df_nasdaq =\
   model evalution forecasting(model path = nasdag model path,\
                           df path = nasdag df path,
                           window size = 70,
```

```
training data size = 0.8,
                         future_days = 5,
                         stock name = 'NASDAQ',
                         ci = 0.99949)
ftse_model_path = "FTSE_MODEL_PATH"
df_ftse, train_ftse, valid_ftse, valid1_ftse, forecast_df_ftse =\
   model_evalution_forecasting(model_path = ftse_model_path,\
                         df path = ftse df path,
                         window_size = 60,
                         training data size = 0.8,
                         future_days = 5,
                         stock name = 'FTSE',
                         ci = 0.99949)
nifty model path = "NIFTY MODEL PATH"
df nifty, train nifty, valid nifty, valid1 nifty, forecast df nifty =\
   model evalution_forecasting(model_path = nifty_model_path,\
                         df path = nifty df path,
                         window_size = 30,
                         training data size = 0.8,
                         future_days = 5,
                         stock_name = 'NIFTY50',
                         ci = 0.99949)
#-----#
# </>
```