## Replicated Financial Data Time Series Forecasting Code

## **Data Loading**

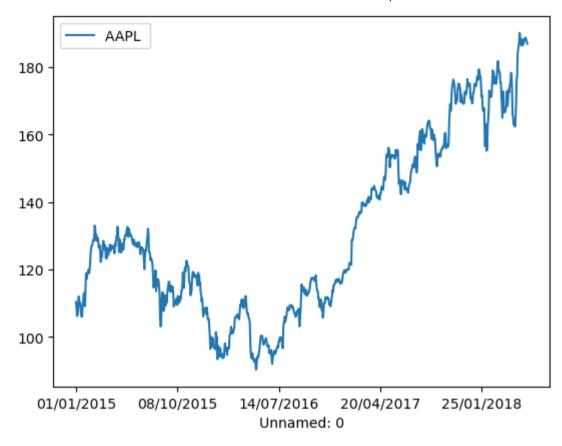
```
In [1]:
         import numpy as np
         import pandas as pd
         data = pd.read csv("https://raw.githubusercontent.com/ritvik02/Financial-Data-Time-Series-Forecasting-Using-Neural-Networks/main/
         data.head()
Out[2]:
            Unnamed:
                                                                      ABT ACN ... XLNX XOM XRAY
                                           AAPL ABBV
                                                         ABC ABMD
                                                                                                           XRX
                                                                                                                 XYL
                                                                                                                        YUM
                                                                                                                                ZBH
                                                                                                                                      ZION
                                                                                                                                             ZTS
         0 01/01/2015 40.94 53.630 159.28 110.38
                                                        90.16
                                                                38.06 45.02 89.31 ... 43.290 92.45 53.27 36.5155 38.07
                                                  65.44
                                                                                                                      52.3831 113.42 28.510 43.03
         1 02/01/2015 40.56 53.910 158.56
                                          109.33
                                                  65.89
                                                        90.46
                                                                     44.90 88.84 ... 43.600 92.83 51.93 36.2257 38.08
                                                                                                                      52.0236 112.59 28.290 43.31
         2 05/01/2015 39.80 53.875 156.47
                                          106.25
                                                  64.65
                                                        89.69
                                                                37.07 44.91 87.34 ... 42.795 90.29
                                                                                                 51.57 35.4353 35.71
                                                                                                                      50.9666 116.79
                                                        90.18
         3 06/01/2015 39.18 53.040 156.36 106.26
                                                  64.33
                                                                36.13 44.40 86.71 ... 42.180 89.81 50.93 34.9611 35.50
                                                                                                                     50.3410 115.80 26.190 42.63
         4 07/01/2015 39.70 53.010 159.72 107.75 66.93 91.98
                                                               37.28 44.76 88.53 ... 42.195 90.72 52.25 35.4089 35.78 52.0092 118.68 26.435 43.51
        5 \text{ rows} \times 507 \text{ columns}
         data.columns
In [3]:
         Index(['Unnamed: 0', 'A ', 'AAL ', 'AAP ', 'AAPL ', 'ABBV ', 'ABC ', 'ABMD ',
Out[3]:
                 'ABT ', 'ACN ',
                'XLNX ', 'XOM ', 'XRAY ', 'XRX ', 'XYL ', 'YUM ', 'ZBH ', 'ZION ',
                'ZTS ', 'Cash'],
               dtype='object', length=507)
```

```
In [4]: # sum of null values in the data
        data.isna().sum()
        Unnamed: 0
Out[4]:
                      0
        AAL
        AAP
        AAPL
        YUM
        ZBH
        ZION
        ZTS
        Cash
        Length: 507, dtype: int64
In [5]: # # converting date column from object to datetime
        # data['Unnamed: 0'] = pd.to datetime(data['Unnamed: 0'])
```

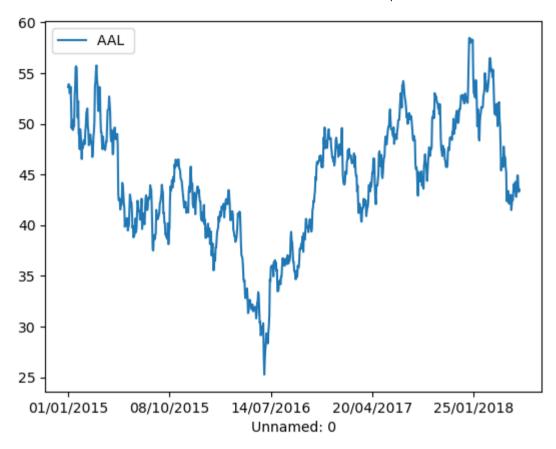
# **Trend Analysis**

```
import matplotlib.pyplot as plt

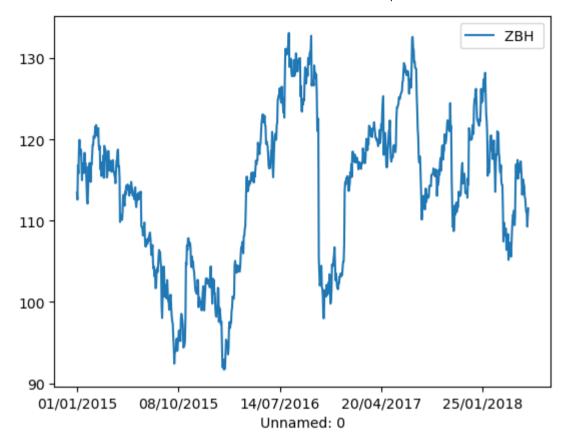
# using matplotlib to plot the data
data.plot.line(x = 'Unnamed: 0', y = 'AAPL ')
plt.show()
```



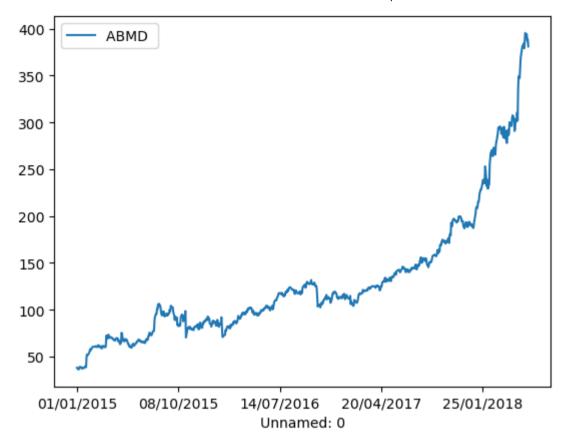
```
In [7]: # using matplotlib to plot the data
data.plot.line(x = 'Unnamed: 0', y = 'AAL ')
plt.show()
```



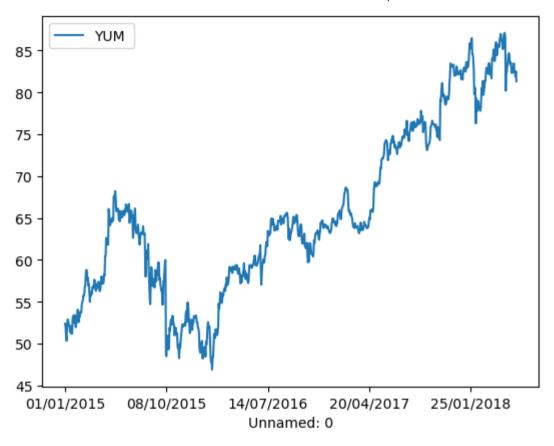
```
In [8]: # using matplotlib to plot the data
data.plot.line(x = 'Unnamed: 0', y = 'ZBH ')
plt.show()
```



```
In [9]: # using matplotlib to plot the data
data.plot.line(x = 'Unnamed: 0', y = 'ABMD ')
plt.show()
```



```
In [10]: # using matplotlib to plot the data
data.plot.line(x = 'Unnamed: 0', y = 'YUM ')
plt.show()
```



# Selecting stock

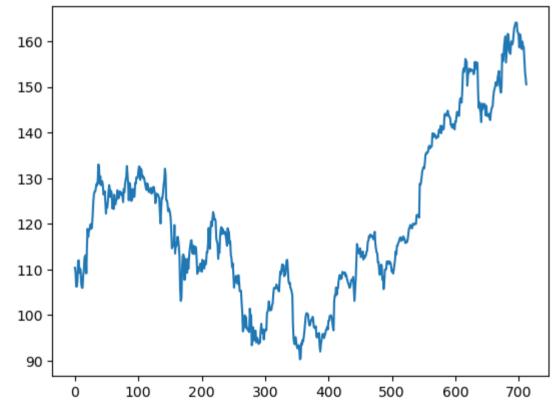
```
In [11]: data_stock = data['AAPL ']
In [12]: data_stock.shape
Out[12]: (891,)
In [13]: 891 - 178
Out[13]: 713
```

```
In [14]: data_stock_np = np.array(data_stock)

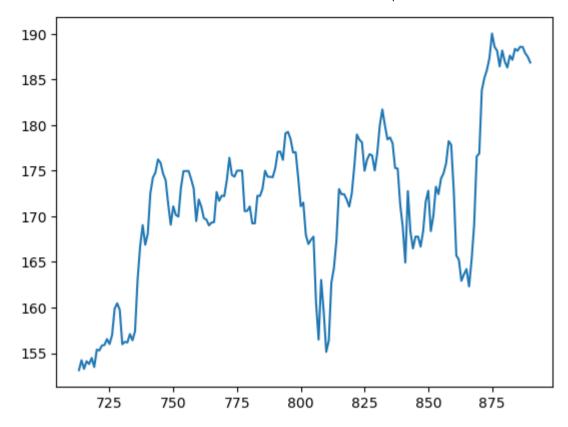
In [15]: data_stock_np[-15]

Out[15]: 188.59

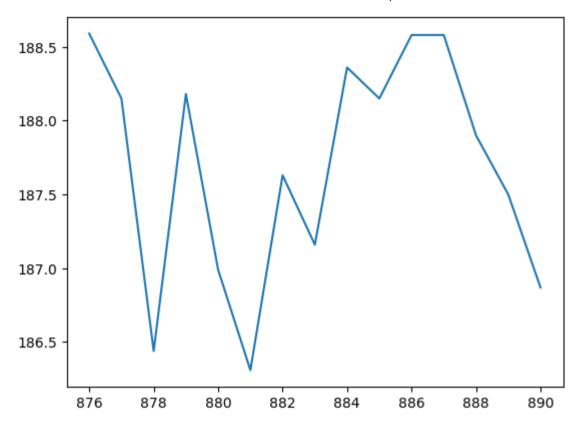
In [16]: data_stock[:713].plot.line(x = 'Unnamed: 0', y = 'AAPL ')
    plt.show()
```



```
In [17]: data_stock[-178:].plot.line(x = 'Unnamed: 0', y = 'AAPL ')
    plt.show()
```



```
In [18]: data_stock[-15:].plot.line(x = 'Unnamed: 0', y = 'AAPL ')
    plt.show()
```



# **Utility function**

```
In [19]:

from pandas import Series
from pandas import concat
from pandas import read_csv
import datetime
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, Bidirectional
from keras.layers import LSTM
from math import sqrt
from matplotlib import pyplot
import numpy
from tensorflow.keras import layers
```

```
# converting the series data to supervised data
def series data to supervised data(data, lag=1):
        df = pd.DataFrame(data)
        columns = [df.shift(i) for i in range(1, lag+1)]
        columns.append(df)
        df = concat(columns, axis=1)
        df.fillna(0, inplace=True)
        return df
# finding difference between rows
def difference(dataset, interval=1):
        diff = list()
        for i in range(interval, len(dataset)):
                value = dataset[i] - dataset[i - interval]
                diff.append(value)
        return Series(diff)
# inverting the difference value
def inverse the difference(history data, yhat, interval=1):
  return (yhat+history data[-interval])
# scaling the difference
def scale(train, test):
        # scaler
        scaler = MinMaxScaler(feature range=(-1, 1))
        scaler = scaler.fit(train)
        train = train.reshape(train.shape[0], train.shape[1])
        train scaled = scaler.transform(train)
        test = test.reshape(test.shape[0], test.shape[1])
        test scaled = scaler.transform(test)
        return scaler, train scaled, test scaled
# inverse the scaling
def invert scale(scaler, X, value):
        temp = [x \text{ for } x \text{ in } X] + [value]
        array = numpy.array(temp)
        array = array.reshape(1, len(array))
        data inverted = scaler.inverse transform(array)
        return data inverted[0, -1]
```

```
# LSTM modeL
def fit lstm(train, batchSize, epoch, neurons):
        X, y = train[:, 0:-1], train[:, -1]
        X = X.reshape(X.shape[0], 1, X.shape[1])
        model = Sequential()
        model.add(LSTM(neurons, batch input shape=(batchSize, X.shape[1], X.shape[2]), stateful=True))
        model.add(Dense(1))
        model.compile(loss='mean squared error', optimizer='adam')
        for i in range(epoch):
                model.fit(X, y, epochs=1, batch size=batchSize, verbose=0, shuffle=False)
                model.reset states()
        return model
# make a one-step forecast
def forecast lstm(model, batch size, X):
        X = X.reshape(1, 1, len(X))
        yhat = model.predict(X, batch size=batch size)
        return vhat[0,0]
def fit rnn(train,batchSize,epoch, neurons):
 X, y = train[:, 0:-1], train[:, -1]
 X = X.reshape(X.shape[0], 1, X.shape[1])
 #RNN modeL
 print("X.shape[1]), ",X.shape[1])
 print("X.shape[2]) ",X.shape[2])
 model = Sequential()
 model.add(layers.SimpleRNN(neurons, batch input shape=(batchSize, X.shape[1], X.shape[2])))
 model.add(layers.Dense(1))
  model.compile(loss='mean squared error', optimizer='adam')
 for i in range(epoch):
    model.fit(X, y, epochs=1, batch size=batchSize, verbose=0, shuffle=False )
   model.reset states()
 return model
# make a one-step forecast
def forecast lstm(model, batch size, X):
```

```
X = X.reshape(1, 1, len(X))
       yhat = model.predict(X, batch size=batch size)
        return vhat[0,0]
# make a one-step forecast
def forecast rnn(model, batch size, X):
        X = X.reshape(1, 1, len(X))
       yhat = model.predict(X, batch size=batch size)
        return yhat[0,0]
def fit cnn(train,batchSize,epoch, neurons):
 X, y = train[:, 0:-1], train[:, -1]
 X = X.reshape(X.shape[0], 1, X.shape[1])
 print("X.shape[1]), ",X.shape[1])
 print("X.shape[2]) ",X.shape[2])
 #CNN model
 model = Sequential()
 model.add(layers.Conv1D(neurons,1, batch input shape=(batchSize, X.shape[1], X.shape[2])))
 model.add(layers.GlobalMaxPooling1D())
 model.add(layers.Dense(1))
 model.compile(loss='mean squared error', optimizer='adam')
  #model.add(layers.Dense(3, activation='sigmoid'))
 for i in range(epoch):
   model.fit(X, y, epochs=1, batch size=batchSize, verbose=0, shuffle=False )
   model.reset states()
 return model
# make a one-step forecast
def forecast cnn(model, batch size, X):
       X = X.reshape(1, 1, len(X))
        yhat = model.predict(X, batch size=batch size)
        return vhat[0,0]
def fit bilstm(train,batchSize,epoch, neurons):
 X, y = train[:, 0:-1], train[:, -1]
 X = X.reshape(X.shape[0], 1, X.shape[1])
 model = Sequential()
```

```
print("X.shape[1]), ",X.shape[1])
 print("X.shape[2]) ",X.shape[2])
 # Bi LSTM ModeL
 model = Sequential()
 model.add(Bidirectional(LSTM(neurons, batch input shape=(batchSize, X.shape[1], X.shape[2]), stateful=True)))
 model.add(Dense(1))
 model.compile(loss='mean squared error', optimizer='adam')
 #model.add(layers.Dense(3, activation='sigmoid'))
 for i in range(epoch):
   model.fit(X, y, epochs=1, batch size=batchSize, verbose=0, shuffle=False )
   model.reset states()
 return model
# make a one-step forecast
def forecast bilstm(model, batch size, X):
        X = X.reshape(1, 1, len(X))
       yhat = model.predict(X, batch size=batch size)
        return yhat[0,0]
```

#### **LSTM**

```
In [20]: data_stock.shape
Out[20]: (891,)

In [21]: 0.20 * 891
Out[21]: 178.2000000000002

In [22]: # modify data to be stationary
    raw_values = np.array(data_stock)
    diff_values = difference(raw_values, 1)
    # modify data to be supervised
    supervised = series_data_to_supervised_data(diff_values, 1)
    supervised_values = supervised.values
```

```
# split data
train, test = supervised values[0:-178], supervised values[-178:]
# modify the scale of the data
scaler, train scaled, test scaled = scale(train, test)
# fit the model
lstm model = fit lstm(train scaled, 1, 1, 4)
# forecast
train reshaped = train scaled[:, 0].reshape(len(train scaled), 1, 1)
lstm model.predict(train reshaped, batch size=1)
# walk-forward validation on the test data
predictions = list()
for i in range(len(test scaled)):
        # make one-step forecast
       X, y = test scaled[i, 0:-1], test scaled[i, -1]
        yhat = forecast lstm(lstm model, 1, X)
        # invert scaling
        yhat = invert scale(scaler, X, yhat)
        vhat = inverse the difference(raw values, vhat, len(test scaled)-i+1)
        # store forecast
        predictions.append(yhat)
        expected = raw values[len(train) + i + 1]
        #print('Month=%d, Predicted=%f, Expected=%f' % (i+1, vhat, expected))
##print("X and y data: ", X," y = ", y)
#print("yhat = ", yhat)
# report performance
rmse = sqrt(mean squared error(raw values[-178:], predictions))
print('\n Test RMSE: %.3f' % rmse)
# line plot of observed vs predicted
pyplot.plot(raw values[-178:])
pyplot.plot(predictions)
pyplot.show()
```

```
1/1 [======= ] - 0s 29ms/step
1/1 [======= ] - 0s 33ms/step
1/1 [======= ] - 0s 33ms/step
1/1 [======= ] - Os 30ms/step
1/1 [======= ] - Os 32ms/step
1/1 [======== ] - 0s 31ms/step
1/1 [======= ] - 0s 32ms/step
1/1 [======= ] - Os 32ms/step
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1/1 [======== ] - 0s 33ms/step
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1/1 [======= ] - 0s 32ms/step
1/1 [======= ] - 0s 34ms/step
1/1 [======= ] - 0s 29ms/step
1/1 [======== ] - 0s 30ms/step
1/1 [======= ] - Os 30ms/step
1/1 [======== ] - 0s 34ms/step
1/1 [======= ] - 0s 33ms/step
1/1 [======= ] - Os 28ms/step
```

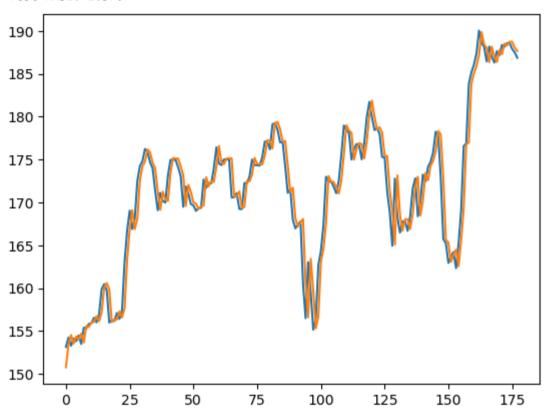
```
1/1 [======= ] - 0s 31ms/step
1/1 [======= ] - 0s 30ms/step
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```

```
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1/1 [======= ] - Os 35ms/step
1/1 [======== ] - 0s 29ms/step
1/1 [======= ] - 0s 36ms/step
1/1 [======= ] - Os 34ms/step
```

```
1/1 [=======] - 0s 37ms/step
1/1 [=======] - 0s 34ms/step
1/1 [========] - 0s 34ms/step
```

Test RMSE: 2.370



#### Over 15 test rows

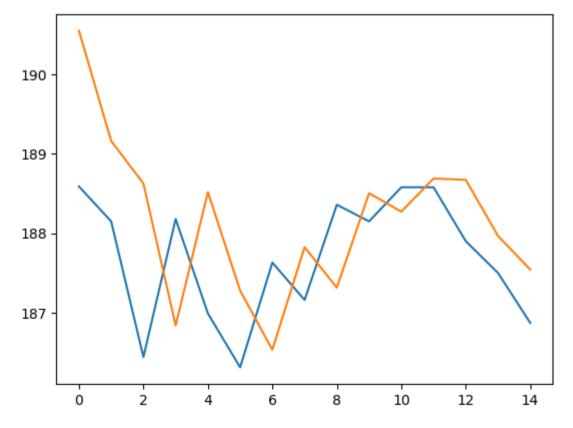
```
In [23]: # modify data to be stationary
    raw_values = np.array(data_stock)
    diff_values = difference(raw_values, 1)
    # modify data to be supervised
    supervised = series_data_to_supervised_data(diff_values, 1)
    supervised_values = supervised.values

# split data
```

```
train, test = supervised values[0:-15], supervised values[-15:]
# modify the scale of the data
scaler, train scaled, test scaled = scale(train, test)
# fit the model
lstm model = fit lstm(train scaled, 1, 1, 4)
# forecast
train reshaped = train scaled[:, 0].reshape(len(train scaled), 1, 1)
lstm model.predict(train reshaped, batch size=1)
# walk-forward validation on the test data
predictions = list()
for i in range(len(test scaled)):
        # make one-step forecast
       X, y = \text{test scaled}[i, 0:-1], test scaled[i, -1]
        yhat = forecast lstm(lstm model, 1, X)
        # invert scaling
        vhat = invert scale(scaler, X, yhat)
        yhat = inverse the difference(raw values, yhat, len(test scaled)-i+1)
        # store forecast
        predictions.append(yhat)
        expected = raw values[len(train) + i + 1]
        #print('Month=%d, Predicted=%f, Expected=%f' % (i+1, yhat, expected))
##print("X and y data : ", X ," y = ", y )
#print("yhat = ", yhat)
# report performance
rmse = sqrt(mean squared error(raw values[-15:], predictions))
print('\n Test RMSE: %.3f' % rmse)
# line plot of observed vs predicted
pyplot.plot(raw values[-15:])
pyplot.plot(predictions)
pyplot.show()
```

```
875/875 [============ ] - 2s 2ms/step
1/1 [========]
             - 0s 32ms/step
             - 0s 35ms/step
             - 0s 30ms/step
1/1 [=======]
             - 0s 31ms/step
             - 0s 32ms/step
             - 0s 35ms/step
             - 0s 38ms/step
1/1 [======= ] - 0s 31ms/step
1/1 [======= ] - 0s 31ms/step
```

Test RMSE: 1.125



#### RNN

```
In [24]: raw values = np.array(data stock)
          diff values = difference(raw values, 1)
         # modify data to be supervised
          supervised = series data to supervised data(diff values, 1)
          supervised values = supervised.values
          # split data
          train, test = supervised values[0:-178], supervised values[-178:]
          # modify the scale of the data
          scaler, train scaled, test scaled = scale(train, test)
          # fit the model
         lstm model = fit rnn(train scaled, 1, 1, 4)
          # forecast
          train reshaped = train scaled[:, 0].reshape(len(train scaled), 1, 1)
          lstm model.predict(train reshaped, batch size=1)
          # walk-forward validation on the test data
          predictions = list()
         for i in range(len(test scaled)):
                 # make one-step forecast
                 X, y = test scaled[i, 0:-1], test scaled[i, -1]
                 yhat = forecast rnn(lstm model, 1, X)
                 # invert scaling
                 yhat = invert scale(scaler, X, yhat)
                 yhat = inverse the difference(raw values, yhat, len(test scaled)-i+1)
                 # store forecast
                  predictions.append(yhat)
                  expected = raw values[len(train) + i + 1]
                 print('Month=%d, Predicted=%f, Expected=%f' % (i+1, yhat, expected))
          ##print("X and y data: ", X , " y = ", y )
          #print("yhat = ", yhat)
         # report performance
          rmse = sqrt(mean squared error(raw values[-178:], predictions))
```

```
print('\n Test RMSE: %.3f' % rmse)
# line plot of observed vs predicted
pyplot.plot(raw_values[-178:])
pyplot.plot(predictions)
pyplot.show()
```

```
X.shape[1]), 1
X.shape[2]) 1
712/712 [========== ] - 1s 2ms/step
Month=1, Predicted=150.858546, Expected=153.140000
1/1 [======= ] - 0s 31ms/step
Month=2, Predicted=153.036291, Expected=154.230000
Month=3, Predicted=154.275633, Expected=153.280000
Month=4, Predicted=153.547355, Expected=154.120000
1/1 [======== ] - 0s 35ms/step
Month=5, Predicted=154.192395, Expected=153.810000
Month=6, Predicted=154.008013, Expected=154.480000
Month=7, Predicted=154.570775, Expected=153.480000
Month=8, Predicted=153.752692, Expected=155.390000
Month=9, Predicted=155.351098, Expected=155.300000
1/1 [======= ] - 0s 36ms/step
Month=10, Predicted=155.473905, Expected=155.840000
1/1 [======] - 0s 31ms/step
Month=11, Predicted=155.944907, Expected=155.900000
Month=12, Predicted=156.057445, Expected=156.550000
1/1 [======== ] - 0s 32ms/step
Month=13, Predicted=156.642945, Expected=156.000000
1/1 [============= ] - 0s 36ms/step
Month=14, Predicted=156.224198, Expected=156.990000
Month=15, Predicted=157.046295, Expected=159.880000
1/1 [======= ] - 0s 31ms/step
Month=16, Predicted=159.749618, Expected=160.470000
1/1 [======= ] - 0s 31ms/step
Month=17, Predicted=160.569465, Expected=159.760000
1/1 [======= ] - 0s 34ms/step
Month=18, Predicted=160.001548, Expected=155.980000
1/1 [======= ] - 0s 31ms/step
Month=19, Predicted=156.508405, Expected=156.250000
Month=20, Predicted=156.384414, Expected=156.170000
```

Month=21, Predicted=156.342808, Expected=157.100000 1/1 [======= ] - Os 32ms/step Month=22, Predicted=157.162721, Expected=156.410000 1/1 [======= ] - 0s 38ms/step Month=23, Predicted=156.649385, Expected=157.410000 Month=24, Predicted=157.465226, Expected=163.050000 1/1 [======= ] - 0s 34ms/step Month=25, Predicted=162.743349, Expected=166.720000 Month=26, Predicted=166.526611, Expected=169.040000 1/1 [======== ] - 0s 33ms/step Month=27, Predicted=168.961343, Expected=166.890000 1/1 [======= ] - 0s 33ms/step Month=28, Predicted=167.279906, Expected=168.110000 Month=29, Predicted=168.141868, Expected=172.500000 Month=30, Predicted=172.257352, Expected=174.250000 Month=31, Predicted=174.227117, Expected=174.810000 1/1 [======= ] - 0s 36ms/step Month=32, Predicted=174.912729, Expected=176.240000 1/1 [======] - 0s 37ms/step Month=33, Predicted=176.249891, Expected=175.880000 Month=34, Predicted=176.083480, Expected=174.670000 1/1 [======== ] - 0s 39ms/step Month=35, Predicted=174.964934, Expected=173.970000 1/1 [======= ] - 0s 35ms/step Month=36, Predicted=174.210467, Expected=171.340000 Month=37, Predicted=171.774628, Expected=169.080000 1/1 [======= ] - 0s 34ms/step Month=38, Predicted=169.480411, Expected=171.100000 1/1 [======= ] - 0s 34ms/step Month=39, Predicted=171.050243, Expected=170.150000 Month=40, Predicted=170.417355, Expected=169.980000 1/1 [======= ] - 0s 31ms/step Month=41, Predicted=170.162679, Expected=173.140000 1/1 [======= ] - 0s 34ms/step Month=42, Predicted=172.986733, Expected=174.960000 

Month=43, Predicted=174.930076, Expected=174.960000 1/1 [======= ] - Os 32ms/step Month=44, Predicted=175.124030, Expected=174.970000 Month=45, Predicted=175.132932, Expected=174.090000 Month=46, Predicted=174.349859, Expected=173.070000 Month=47, Predicted=173.344823, Expected=169.480000 Month=48, Predicted=169.994333, Expected=171.850000 1/1 [======== ] - 0s 31ms/step Month=49, Predicted=171.766633, Expected=171.050000 Month=50, Predicted=171.301260, Expected=169.800000 Month=51, Predicted=170.099136, Expected=169.640000 1/1 [======= ] - 0s 34ms/step Month=52, Predicted=169.821582, Expected=169.010000 Month=53, Predicted=169.242886, Expected=169.320000 1/1 [======= ] - 0s 31ms/step Month=54, Predicted=169.450033, Expected=169.370000 1/1 [======] - 0s 31ms/step Month=55, Predicted=169.528542, Expected=172.670000 1/1 [======= ] - 0s 31ms/step Month=56, Predicted=172.505305, Expected=171.700000 1/1 [======== ] - 0s 32ms/step Month=57, Predicted=171.969492, Expected=172.270000 1/1 [======= ] - 0s 34ms/step Month=58, Predicted=172.371641, Expected=172.220000 Month=59, Predicted=172.389517, Expected=173.970000 1/1 [======= ] - 0s 32ms/step Month=60, Predicted=173.947117, Expected=176.420000 Month=61, Predicted=176.329162, Expected=174.540000 Month=62, Predicted=174.903528, Expected=174.350000 Month=63, Predicted=174.534871, Expected=175.010000 1/1 [======= ] - 0s 41ms/step Month=64, Predicted=175.101860, Expected=175.010000 

Month=65, Predicted=175.174030, Expected=175.010000 1/1 [======] - 0s 35ms/step Month=66, Predicted=175.174030, Expected=170.570000 1/1 [======= ] - Os 33ms/step Month=67, Predicted=171.142619, Expected=170.600000 1/1 [======= ] - 0s 34ms/step Month=68, Predicted=170.760737, Expected=171.080000 1/1 [======= ] - 0s 38ms/step Month=69, Predicted=171.191449, Expected=169.230000 Month=70, Predicted=169.590547, Expected=169.230000 1/1 [======== ] - 0s 32ms/step Month=71, Predicted=169.394030, Expected=172.260000 1/1 [======= ] - 0s 38ms/step Month=72, Predicted=172.117615, Expected=172.230000 Month=73, Predicted=172.397322, Expected=173.030000 1/1 [======= ] - 0s 29ms/step Month=74, Predicted=173.106708, Expected=175.000000 1/1 [======= ] - 0s 34ms/step Month=75, Predicted=174.955161, Expected=174.350000 1/1 [======= ] - 0s 37ms/step Month=76, Predicted=174.585054, Expected=174.330000 1/1 [======] - 0s 34ms/step Month=77, Predicted=174.496225, Expected=174.290000 1/1 [======= ] - 0s 34ms/step Month=78, Predicted=174.458419, Expected=175.280000 1/1 [======== ] - 0s 32ms/step Month=79, Predicted=175.336295, Expected=177.090000 1/1 [======= ] - 0s 29ms/step Month=80, Predicted=177.061079, Expected=177.090000 1/1 [======= ] - Os 32ms/step Month=81, Predicted=177.254030, Expected=176.190000 1/1 [======= ] - 0s 31ms/step Month=82, Predicted=176.452004, Expected=179.100000 Month=83, Predicted=178.967885, Expected=179.260000 Month=84, Predicted=179.406473, Expected=178.460000 Month=85, Predicted=178.711260, Expected=177.000000 1/1 [======= ] - 0s 31ms/step Month=86, Predicted=177.320993, Expected=177.040000 

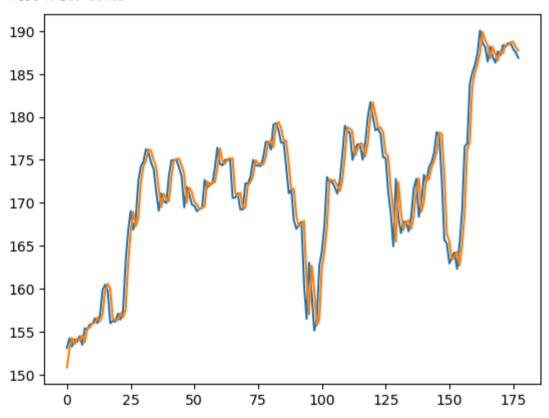
Month=87, Predicted=177.199640, Expected=174.220000 1/1 [======= ] - Os 31ms/step Month=88, Predicted=174.671485, Expected=171.110000 1/1 [======= ] - Os 31ms/step Month=89, Predicted=171.586215, Expected=171.510000 Month=90, Predicted=171.630186, Expected=167.960000 Month=91, Predicted=168.471295, Expected=166.970000 Month=92, Predicted=167.241626, Expected=167.430000 1/1 [======== ] - 0s 29ms/step Month=93, Predicted=167.543631, Expected=167.780000 Month=94, Predicted=167.905654, Expected=160.500000 Month=95, Predicted=161.180099, Expected=156.490000 1/1 [======= ] - 0s 39ms/step Month=96, Predicted=157.034645, Expected=163.030000 1/1 [======= ] - Os 36ms/step Month=97, Predicted=162.693890, Expected=159.540000 1/1 [======= ] - 0s 33ms/step Month=98, Predicted=160.046691, Expected=155.150000 1/1 [======] - 0s 33ms/step Month=99, Predicted=155.719528, Expected=156.410000 1/1 [======= ] - 0s 31ms/step Month=100, Predicted=156.437656, Expected=162.710000 1/1 [======= ] - 0s 33ms/step Month=101, Predicted=162.380442, Expected=164.340000 1/1 [======= ] - 0s 32ms/step Month=102, Predicted=164.329297, Expected=167.370000 1/1 [======= ] - 0s 39ms/step Month=103, Predicted=167.227615, Expected=172.990000 1/1 [======= ] - 0s 31ms/step Month=104, Predicted=172.684158, Expected=172.430000 1/1 [======= ] - 0s 34ms/step Month=105, Predicted=172.655285, Expected=172.430000 1/1 [======= ] - 0s 37ms/step Month=106, Predicted=172.594030, Expected=171.850000 1/1 [======= ] - 0s 33ms/step Month=107, Predicted=172.077458, Expected=171.070000 1/1 [======= ] - 0s 32ms/step Month=108, Predicted=171.319105, Expected=172.500000 1/1 [======= ] - 0s 35ms/step

Month=109, Predicted=172.509891, Expected=175.500000 1/1 [======= ] - 0s 40ms/step Month=110, Predicted=175.360162, Expected=178.970000 1/1 [======= ] - 0s 30ms/step Month=111, Predicted=178.791846, Expected=178.390000 1/1 [======= ] - 0s 34ms/step Month=112, Predicted=178.617458, Expected=178.120000 1/1 [======= ] - 0s 32ms/step Month=113, Predicted=178.313635, Expected=175.000000 Month=114, Predicted=175.477046, Expected=176.210000 1/1 [======= ] - 0s 46ms/step Month=115, Predicted=176.242923, Expected=176.820000 1/1 [======= ] - 0s 33ms/step Month=116, Predicted=176.917290, Expected=176.670000 Month=117, Predicted=176.850486, Expected=175.030000 1/1 [======= ] - 0s 31ms/step Month=118, Predicted=175.369428, Expected=176.940000 1/1 [======= ] - 0s 40ms/step Month=119, Predicted=176.901098, Expected=179.980000 1/1 [======= ] - 0s 39ms/step Month=120, Predicted=179.836769, Expected=181.720000 1/1 [======= ] - 0s 39ms/step Month=121, Predicted=181.698126, Expected=179.970000 1/1 [======= ] - 0s 34ms/step Month=122, Predicted=180.320545, Expected=178.440000 1/1 [======= ] - 0s 32ms/step Month=123, Predicted=178.768197, Expected=178.650000 1/1 [======= ] - 0s 28ms/step Month=124, Predicted=178.790990, Expected=178.020000 1/1 [======= ] - 0s 31ms/step Month=125, Predicted=178.252886, Expected=175.300000 1/1 [======= ] - 0s 40ms/step Month=126, Predicted=175.742676, Expected=175.240000 1/1 [======= ] - 0s 38ms/step Month=127, Predicted=175.410614, Expected=171.270000 1/1 [======= ] - 0s 37ms/step Month=128, Predicted=171.811884, Expected=168.850000 1/1 [======= ] - 0s 38ms/step Month=129, Predicted=169.265425, Expected=164.940000 1/1 [======= ] - 0s 29ms/step Month=130, Predicted=165.477693, Expected=172.770000 1/1 [======= ] - 0s 31ms/step

Month=131, Predicted=172.413504, Expected=168.340000 1/1 [======] - 0s 32ms/step Month=132, Predicted=168.912004, Expected=166.480000 1/1 [======= ] - 0s 36ms/step Month=133, Predicted=166.841541, Expected=167.780000 1/1 [======= ] - 0s 39ms/step Month=134, Predicted=167.803456, Expected=167.780000 1/1 [======= ] - 0s 34ms/step Month=135, Predicted=167.944030, Expected=166.680000 Month=136, Predicted=166.963320, Expected=168.390000 1/1 [======= ] - 0s 33ms/step Month=137, Predicted=168.371161, Expected=171.610000 1/1 [======= ] - 0s 32ms/step Month=138, Predicted=171.451798, Expected=172.800000 Month=139, Predicted=172.835035, Expected=168.380000 1/1 [======= ] - 0s 37ms/step Month=140, Predicted=168.951388, Expected=170.050000 1/1 [======] - 0s 38ms/step Month=141, Predicted=170.035222, Expected=173.250000 1/1 [======= ] - 0s 37ms/step Month=142, Predicted=173.093437, Expected=172.440000 1/1 [======] - 0s 32ms/step Month=143, Predicted=172.692337, Expected=174.140000 1/1 [======= ] - 0s 33ms/step Month=144, Predicted=174.122175, Expected=174.730000 1/1 [======= ] - 0s 30ms/step Month=145, Predicted=174.829465, Expected=175.820000 1/1 [======= ] - 0s 32ms/step Month=146, Predicted=175.865633, Expected=178.240000 Month=147, Predicted=178.151954, Expected=177.840000 1/1 [======= ] - 0s 32ms/step Month=148, Predicted=178.047850, Expected=172.800000 1/1 [======= ] - 0s 30ms/step Month=149, Predicted=173.406378, Expected=165.720000 1/1 [======= ] - 0s 39ms/step Month=150, Predicted=166.396619, Expected=165.240000 1/1 [======= ] - 0s 34ms/step Month=151, Predicted=165.456577, Expected=162.940000 1/1 [======= ] - 0s 31ms/step Month=152, Predicted=163.344194, Expected=163.650000 

Month=153, Predicted=163.736439, Expected=164.220000 1/1 [======] - 0s 38ms/step Month=154, Predicted=164.321641, Expected=162.320000 1/1 [======= ] - 0s 33ms/step Month=155, Predicted=162.685509, Expected=165.260000 1/1 [======= ] - 0s 38ms/step Month=156, Predicted=165.125297, Expected=169.100000 1/1 [======= ] - 0s 42ms/step Month=157, Predicted=168.894183, Expected=176.570000 Month=158, Predicted=176.216824, Expected=176.890000 1/1 [======= ] - 0s 35ms/step Month=159, Predicted=177.018938, Expected=183.830000 1/1 [======= ] - 0s 32ms/step Month=160, Predicted=183.484976, Expected=185.160000 1/1 [======= ] - 0s 31ms/step Month=161, Predicted=185.180314, Expected=186.050000 Month=162, Predicted=186.117015, Expected=187.360000 Month=163, Predicted=187.382408, Expected=190.040000 1/1 [======= ] - 0s 34ms/step Month=164, Predicted=189.928157, Expected=188.590000 Month=165, Predicted=188.909960, Expected=188.150000 1/1 [======= ] - 0s 40ms/step Month=166, Predicted=188.362216, Expected=186.440000 1/1 [======= ] - 0s 42ms/step Month=167, Predicted=186.786516, Expected=188.180000 1/1 [======= ] - 0s 34ms/step Month=168, Predicted=188.158126, Expected=186.990000 1/1 [======= ] - 0s 39ms/step Month=169, Predicted=187.282829, Expected=186.310000 1/1 [======= ] - 0s 34ms/step Month=170, Predicted=186.548303, Expected=187.630000 1/1 [======= ] - 0s 33ms/step Month=171, Predicted=187.651361, Expected=187.160000 1/1 [======= ] - 0s 34ms/step Month=172, Predicted=187.375487, Expected=188.360000 Month=173, Predicted=188.393978, Expected=188.150000 Month=174, Predicted=188.337063, Expected=188.580000 1/1 [======= ] - 0s 37ms/step

Test RMSE: 2.412



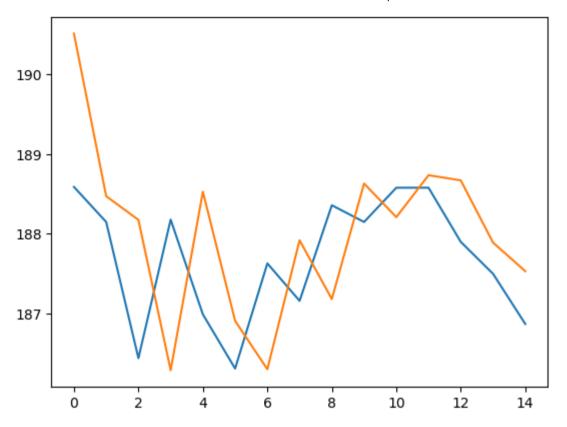
#### Over 15 test rows

```
In [25]: raw_values = np.array(data_stock)
    diff_values = difference(raw_values, 1)
# modify data to be supervised
supervised = series_data_to_supervised_data(diff_values, 1)
```

```
supervised values = supervised.values
# split data
train, test = supervised values[0:-15], supervised values[-15:]
# modify the scale of the data
scaler, train scaled, test scaled = scale(train, test)
# fit the model
lstm model = fit rnn(train scaled, 1, 1, 4)
# forecast
train reshaped = train scaled[:, 0].reshape(len(train scaled), 1, 1)
lstm model.predict(train reshaped, batch size=1)
# walk-forward validation on the test data
predictions = list()
for i in range(len(test scaled)):
       # make one-step forecast
       X, y = test scaled[i, 0:-1], test scaled[i, -1]
       yhat = forecast rnn(lstm model, 1, X)
        # invert scaling
        vhat = invert scale(scaler, X, yhat)
        yhat = inverse the difference(raw values, yhat, len(test scaled)-i+1)
        # store forecast
        predictions.append(yhat)
        expected = raw values[len(train) + i + 1]
        print('Month=%d, Predicted=%f, Expected=%f' % (i+1, yhat, expected))
##print("X and y data : ", X ," y = ", y )
#print("yhat = ", yhat)
# report performance
rmse = sqrt(mean squared_error(raw_values[-15:], predictions))
print('\n Test RMSE: %.3f' % rmse)
# line plot of observed vs predicted
pyplot.plot(raw values[-15:])
pyplot.plot(predictions)
pyplot.show()
```

```
X.shape[1]), 1
X.shape[2]) 1
875/875 [========== ] - 2s 2ms/step
1/1 [======= ] - 0s 31ms/step
Month=1, Predicted=190.515305, Expected=188.590000
Month=2, Predicted=188.473870, Expected=188.150000
Month=3, Predicted=188.176493, Expected=186.440000
Month=4, Predicted=186.289961, Expected=188.180000
1/1 [======== ] - 0s 37ms/step
Month=5, Predicted=188.530675, Expected=186.990000
Month=6, Predicted=186.909095, Expected=186.310000
Month=7, Predicted=186.301352, Expected=187.630000
Month=8, Predicted=187.920263, Expected=187.160000
Month=9, Predicted=187.182069, Expected=188.360000
Month=10, Predicted=188.632629, Expected=188.150000
1/1 [======] - 0s 34ms/step
Month=11, Predicted=188.210663, Expected=188.580000
Month=12, Predicted=188.737146, Expected=188.580000
1/1 [============= ] - 0s 44ms/step
Month=13, Predicted=188.672168, Expected=187.900000
1/1 [======= ] - 0s 34ms/step
Month=14, Predicted=187.891352, Expected=187.500000
Month=15, Predicted=187.532405, Expected=186.870000
```

Test RMSE: 1.109



### **CNN Model**

```
In [26]:
    raw_values = np.array(data_stock)
    diff_values = difference(raw_values, 1)
# modify data to be supervised
supervised = series_data_to_supervised_data(diff_values, 1)
supervised_values = supervised.values

# split data
train, test = supervised_values[0:-178], supervised_values[-178:]

# modify the scale of the data
scaler, train_scaled, test_scaled = scale(train, test)

# fit the model
```

```
cnn model = fit cnn(train scaled, 1, 1, 1)
# forecast
train reshaped = train scaled[:, 0].reshape(len(train scaled), 1, 1)
cnn model.predict(train reshaped, batch size=1)
# walk-forward validation on the test data
predictions = list()
for i in range(len(test scaled)):
       # make one-step forecast
       X, y = test scaled[i, 0:-1], test scaled[i, -1]
       yhat = forecast cnn(cnn model, 1, X)
        # invert scaling
       yhat = invert scale(scaler, X, yhat)
        yhat = inverse the difference(raw values, yhat, len(test scaled)-i+1)
        # store forecast
        predictions.append(yhat)
        expected = raw values[len(train) + i + 1]
        print('Month=%d, Predicted=%f, Expected=%f' % (i+1, vhat, expected))
##print("X and y data: ", X ," y = ", y)
#print("vhat = ", vhat)
# report performance
rmse = sqrt(mean squared error(raw values[-178:], predictions))
print('Test RMSE: %.3f' % rmse)
# line plot of observed vs predicted
pyplot.plot(raw values[-178:])
pyplot.plot(predictions)
pyplot.show()
```

```
X.shape[1]), 1
X.shape[2]) 1
712/712 [========== ] - 1s 2ms/step
Month=1, Predicted=150.999398, Expected=153.140000
Month=2, Predicted=152.803142, Expected=154.230000
1/1 [======= ] - 0s 31ms/step
Month=3, Predicted=154.193240, Expected=153.280000
Month=4, Predicted=153.651373, Expected=154.120000
1/1 [============= ] - 0s 31ms/step
Month=5, Predicted=154.133256, Expected=153.810000
Month=6, Predicted=154.053331, Expected=154.480000
Month=7, Predicted=154.527267, Expected=153.480000
Month=8, Predicted=153.861376, Expected=155.390000
Month=9, Predicted=155.189186, Expected=155.300000
1/1 [======= ] - 0s 28ms/step
Month=10, Predicted=155.499317, Expected=155.840000
1/1 [======] - 0s 36ms/step
Month=11, Predicted=155.913275, Expected=155.900000
1/1 [============= ] - 0s 31ms/step
Month=12, Predicted=156.069307, Expected=156.550000
1/1 [======== ] - 0s 32ms/step
Month=13, Predicted=156.601268, Expected=156.000000
1/1 [======= ] - 0s 37ms/step
Month=14, Predicted=156.291347, Expected=156.990000
Month=15, Predicted=156.973246, Expected=159.880000
Month=16, Predicted=159.483122, Expected=160.470000
1/1 [======= ] - 0s 34ms/step
Month=17, Predicted=160.533272, Expected=159.760000
1/1 [======= ] - 0s 31ms/step
Month=18, Predicted=160.083357, Expected=155.980000
Month=19, Predicted=156.917557, Expected=156.250000
1/1 [======= ] - 0s 31ms/step
Month=20, Predicted=156.377293, Expected=156.170000
```

Month=21, Predicted=156.367316, Expected=157.100000 1/1 [======= ] - Os 35ms/step Month=22, Predicted=157.095250, Expected=156.410000 Month=23, Predicted=156.729356, Expected=157.410000 Month=24, Predicted=157.391245, Expected=163.050000 Month=25, Predicted=162.102943, Expected=166.720000 Month=26, Predicted=166.167072, Expected=169.040000 1/1 [======== ] - 0s 35ms/step Month=27, Predicted=168.757160, Expected=166.890000 1/1 [======= ] - 0s 31ms/step Month=28, Predicted=167.501451, Expected=168.110000 Month=29, Predicted=168.047231, Expected=172.500000 Month=30, Predicted=171.803025, Expected=174.250000 1/1 [======= ] - Os 33ms/step Month=31, Predicted=174.081197, Expected=174.810000 1/1 [======= ] - 0s 36ms/step Month=32, Predicted=174.879274, Expected=176.240000 1/1 [======] - 0s 39ms/step Month=33, Predicted=176.135218, Expected=175.880000 Month=34, Predicted=176.133334, Expected=174.670000 1/1 [======== ] - 0s 33ms/step Month=35, Predicted=175.093389, Expected=173.970000 1/1 [======= ] - 0s 40ms/step Month=36, Predicted=174.291356, Expected=171.340000 1/1 [======= ] - 0s 31ms/step Month=37, Predicted=172.047482, Expected=169.080000 Month=38, Predicted=169.713458, Expected=171.100000 1/1 [======= ] - 0s 34ms/step Month=39, Predicted=170.877179, Expected=170.150000 Month=40, Predicted=170.521373, Expected=169.980000 Month=41, Predicted=170.195322, Expected=173.140000 Month=42, Predicted=172.689105, Expected=174.960000 

Month=43, Predicted=174.777192, Expected=174.960000 1/1 [======= ] - Os 32ms/step Month=44, Predicted=175.141311, Expected=174.970000 Month=45, Predicted=175.149310, Expected=174.090000 1/1 [======= ] - 0s 31ms/step Month=46, Predicted=174.447368, Expected=173.070000 1/1 [======= ] - 0s 34ms/step Month=47, Predicted=173.455377, Expected=169.480000 Month=48, Predicted=170.379545, Expected=171.850000 1/1 [======== ] - 0s 32ms/step Month=49, Predicted=171.557156, Expected=171.050000 1/1 [======= ] - 0s 36ms/step Month=50, Predicted=171.391363, Expected=169.800000 1/1 [======= ] - Os 39ms/step Month=51, Predicted=170.231392, Expected=169.640000 Month=52, Predicted=169.853321, Expected=169.010000 Month=53, Predicted=169.317352, Expected=169.320000 1/1 [======= ] - 0s 33ms/step Month=54, Predicted=169.439290, Expected=169.370000 1/1 [======] - 0s 30ms/step Month=55, Predicted=169.541307, Expected=172.670000 Month=56, Predicted=172.191096, Expected=171.700000 1/1 [============= ] - 0s 31ms/step Month=57, Predicted=172.075374, Expected=172.270000 1/1 [======= ] - Os 34ms/step Month=58, Predicted=172.337274, Expected=172.220000 Month=59, Predicted=172.411314, Expected=173.970000 Month=60, Predicted=173.801197, Expected=176.420000 Month=61, Predicted=176.111151, Expected=174.540000 Month=62, Predicted=175.097433, Expected=174.350000 Month=63, Predicted=174.569323, Expected=175.010000 Month=64, Predicted=175.059268, Expected=175.010000 

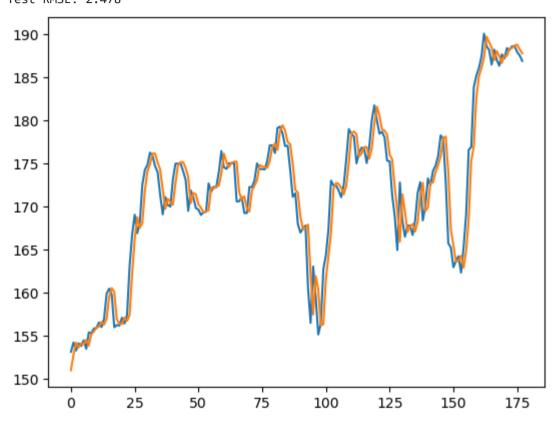
Month=65, Predicted=175.191311, Expected=175.010000 1/1 [======] - 0s 30ms/step Month=66, Predicted=175.191311, Expected=170.570000 1/1 [======= ] - 0s 34ms/step Month=67, Predicted=171.639600, Expected=170.600000 1/1 [======= ] - 0s 31ms/step Month=68, Predicted=170.775309, Expected=171.080000 Month=69, Predicted=171.165279, Expected=169.230000 Month=70, Predicted=169.781431, Expected=169.230000 1/1 [======== ] - 0s 33ms/step Month=71, Predicted=169.411311, Expected=172.260000 Month=72, Predicted=171.835113, Expected=172.230000 Month=73, Predicted=172.417313, Expected=173.030000 Month=74, Predicted=173.051259, Expected=175.000000 1/1 [======= ] - Os 34ms/step Month=75, Predicted=174.787182, Expected=174.350000 1/1 [======= ] - 0s 31ms/step Month=76, Predicted=174.661353, Expected=174.330000 1/1 [======] - 0s 30ms/step Month=77, Predicted=174.515312, Expected=174.290000 Month=78, Predicted=174.479313, Expected=175.280000 1/1 [============= ] - 0s 31ms/step Month=79, Predicted=175.263246, Expected=177.090000 Month=80, Predicted=176.909193, Expected=177.090000 Month=81, Predicted=177.271311, Expected=176.190000 1/1 [======= ] - 0s 31ms/step Month=82, Predicted=176.551369, Expected=179.100000 Month=83, Predicted=178.699121, Expected=179.260000 Month=84, Predicted=179.409300, Expected=178.460000 Month=85, Predicted=178.801363, Expected=177.000000 1/1 [======] - 0s 46ms/step Month=86, Predicted=177.473406, Expected=177.040000 1/1 [======= ] - 0s 31ms/step

Month=87, Predicted=177.213308, Expected=174.220000 1/1 [======= ] - Os 32ms/step Month=88, Predicted=174.965494, Expected=171.110000 Month=89, Predicted=171.913513, Expected=171.510000 Month=90, Predicted=171.611285, Expected=167.960000 Month=91, Predicted=168.851542, Expected=166.970000 Month=92, Predicted=167.349375, Expected=167.430000 1/1 [============= ] - 0s 31ms/step Month=93, Predicted=167.519281, Expected=167.780000 Month=94, Predicted=167.891288, Expected=160.500000 Month=95, Predicted=162.137785, Expected=156.490000 Month=96, Predicted=157.473572, Expected=163.030000 1/1 [======= ] - Os 33ms/step Month=97, Predicted=161.902884, Expected=159.540000 1/1 [======= ] - 0s 32ms/step Month=98, Predicted=160.419538, Expected=155.150000 1/1 [======] - 0s 36ms/step Month=99, Predicted=156.209597, Expected=156.410000 1/1 [======= ] - 0s 30ms/step Month=100, Predicted=156.339229, Expected=162.710000 1/1 [======= ] - 0s 29ms/step Month=101, Predicted=161.630900, Expected=164.340000 1/1 [======= ] - 0s 30ms/step Month=102, Predicted=164.195204, Expected=167.370000 1/1 [======= ] - 0s 29ms/step Month=103, Predicted=166.945113, Expected=172.990000 1/1 [======= ] - 0s 29ms/step Month=104, Predicted=172.046944, Expected=172.430000 1/1 [======= ] - 0s 28ms/step Month=105, Predicted=172.723347, Expected=172.430000 1/1 [======= ] - 0s 32ms/step Month=106, Predicted=172.611311, Expected=171.850000 1/1 [======= ] - 0s 32ms/step Month=107, Predicted=172.147348, Expected=171.070000 1/1 [======= ] - 0s 31ms/step Month=108, Predicted=171.407361, Expected=172.500000 1/1 [======= ] - 0s 31ms/step

Month=109, Predicted=172.395218, Expected=175.500000 Month=110, Predicted=175.081115, Expected=178.970000 1/1 [======= ] - 0s 31ms/step Month=111, Predicted=178.457085, Expected=178.390000 1/1 [======= ] - 0s 34ms/step Month=112, Predicted=178.687348, Expected=178.120000 1/1 [======= ] - 0s 31ms/step Month=113, Predicted=178.355328, Expected=175.000000 Month=114, Predicted=175.805514, Expected=176.210000 1/1 [======= ] - 0s 34ms/step Month=115, Predicted=176.149232, Expected=176.820000 1/1 [======= ] - 0s 29ms/step Month=116, Predicted=176.879271, Expected=176.670000 Month=117, Predicted=176.881320, Expected=175.030000 Month=118, Predicted=175.539418, Expected=176.940000 1/1 [======] - 0s 32ms/step Month=119, Predicted=176.739186, Expected=179.980000 1/1 [======= ] - 0s 33ms/step Month=120, Predicted=179.553113, Expected=181.720000 1/1 [======] - 0s 30ms/step Month=121, Predicted=181.553197, Expected=179.970000 1/1 [======= ] - 0s 32ms/step Month=122, Predicted=180.501425, Expected=178.440000 1/1 [======= ] - 0s 31ms/step Month=123, Predicted=178.927410, Expected=178.650000 1/1 [======= ] - 0s 31ms/step Month=124, Predicted=178.789297, Expected=178.020000 1/1 [======= ] - 0s 34ms/step Month=125, Predicted=178.327352, Expected=175.300000 1/1 [======= ] - 0s 32ms/step Month=126, Predicted=176.025488, Expected=175.240000 1/1 [======= ] - 0s 33ms/step Month=127, Predicted=175.433315, Expected=171.270000 1/1 [======= ] - 0s 34ms/step Month=128, Predicted=172.245569, Expected=168.850000 1/1 [======= ] - 0s 35ms/step Month=129, Predicted=169.515468, Expected=164.940000 1/1 [======= ] - 0s 34ms/step Month=130, Predicted=165.903565, Expected=172.770000 1/1 [======= ] - 0s 36ms/step

Month=131, Predicted=171.384800, Expected=168.340000 1/1 [======] - 0s 30ms/step Month=132, Predicted=169.407599, Expected=166.480000 1/1 [======= ] - 0s 32ms/step Month=133, Predicted=167.033432, Expected=167.780000 1/1 [======= ] - 0s 33ms/step Month=134, Predicted=167.701226, Expected=167.780000 1/1 [======= ] - 0s 35ms/step Month=135, Predicted=167.961311, Expected=166.680000 Month=136, Predicted=167.081382, Expected=168.390000 1/1 [======= ] - 0s 40ms/step Month=137, Predicted=168.229199, Expected=171.610000 1/1 [======= ] - 0s 25ms/step Month=138, Predicted=171.147101, Expected=172.800000 Month=139, Predicted=172.743233, Expected=168.380000 1/1 [======= ] - 0s 29ms/step Month=140, Predicted=169.445599, Expected=170.050000 1/1 [======] - 0s 30ms/step Month=141, Predicted=169.897202, Expected=173.250000 1/1 [======= ] - 0s 33ms/step Month=142, Predicted=172.791102, Expected=172.440000 1/1 [======] - 0s 32ms/step Month=143, Predicted=172.783363, Expected=174.140000 1/1 [======= ] - 0s 33ms/step Month=144, Predicted=173.981200, Expected=174.730000 1/1 [======= ] - 0s 32ms/step Month=145, Predicted=174.793272, Expected=175.820000 1/1 [======= ] - 0s 32ms/step Month=146, Predicted=175.783240, Expected=178.240000 Month=147, Predicted=177.937153, Expected=177.840000 1/1 [======= ] - 0s 34ms/step Month=148, Predicted=178.101337, Expected=172.800000 1/1 [======= ] - 0s 33ms/step Month=149, Predicted=173.989639, Expected=165.720000 1/1 [======= ] - 0s 34ms/step Month=150, Predicted=167.317772, Expected=165.240000 Month=151, Predicted=165.517342, Expected=162.940000 1/1 [======= ] - 0s 29ms/step Month=152, Predicted=163.581461, Expected=163.650000 

Month=153, Predicted=163.689264, Expected=164.220000 1/1 [======= ] - 0s 31ms/step Month=154, Predicted=164.287274, Expected=162.320000 1/1 [======= ] - 0s 32ms/step Month=155, Predicted=162.881434, Expected=165.260000 1/1 [======= ] - 0s 39ms/step Month=156, Predicted=164.853119, Expected=169.100000 1/1 [======= ] - 0s 35ms/step Month=157, Predicted=168.513061, Expected=176.570000 Month=158, Predicted=175.256824, Expected=176.890000 1/1 [======= ] - 0s 30ms/step Month=159, Predicted=177.007290, Expected=183.830000 1/1 [======= ] - 0s 30ms/step Month=160, Predicted=182.622859, Expected=185.160000 Month=161, Predicted=185.075224, Expected=186.050000 1/1 [======= ] - 0s 31ms/step Month=162, Predicted=186.053253, Expected=187.360000 1/1 [======] - 0s 30ms/step Month=163, Predicted=187.279225, Expected=190.040000 1/1 [======= ] - 0s 36ms/step Month=164, Predicted=189.685136, Expected=188.590000 1/1 [======= ] - 0s 27ms/step Month=165, Predicted=189.061405, Expected=188.150000 1/1 [======= ] - 0s 31ms/step Month=166, Predicted=188.419339, Expected=186.440000 1/1 [======= ] - 0s 32ms/step Month=167, Predicted=186.963422, Expected=188.180000 1/1 [======= ] - 0s 39ms/step Month=168, Predicted=188.013197, Expected=186.990000 Month=169, Predicted=187.409388, Expected=186.310000 1/1 [======= ] - 0s 34ms/step Month=170, Predicted=186.627355, Expected=187.630000 1/1 [======= ] - 0s 35ms/step Month=171, Predicted=187.547225, Expected=187.160000 1/1 [======= ] - 0s 35ms/step Month=172, Predicted=187.435341, Expected=188.360000 Month=173, Predicted=188.301232, Expected=188.150000 1/1 [======] - 0s 37ms/step Month=174, Predicted=188.373324, Expected=188.580000 1/1 [======= ] - 0s 45ms/step

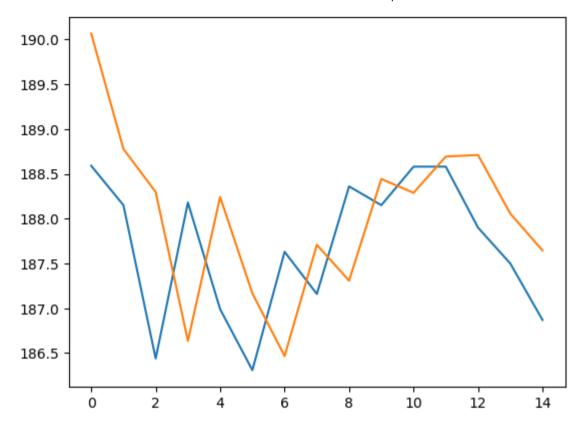


### Over 15 test rows

```
In [27]: raw_values = np.array(data_stock)
    diff_values = difference(raw_values, 1)
# modify data to be supervised
supervised = series_data_to_supervised_data(diff_values, 1)
supervised_values = supervised.values
```

```
# split data
train, test = supervised values[0:-15], supervised values[-15:]
# modify the scale of the data
scaler, train scaled, test scaled = scale(train, test)
# fit the model
cnn model = fit cnn(train scaled, 1, 1, 1)
# forecast
train reshaped = train scaled[:, 0].reshape(len(train scaled), 1, 1)
cnn model.predict(train reshaped, batch size=1)
# walk-forward validation on the test data
predictions = list()
for i in range(len(test scaled)):
        # make one-step forecast
       X, y = \text{test scaled}[i, 0:-1], test scaled[i, -1]
        vhat = forecast cnn(cnn model, 1, X)
        # invert scaling
       yhat = invert scale(scaler, X, yhat)
       yhat = inverse the difference(raw_values, yhat, len(test_scaled)-i+1)
        # store forecast
        predictions.append(yhat)
        expected = raw values[len(train) + i + 1]
        print('Month=%d, Predicted=%f, Expected=%f' % (i+1, yhat, expected))
##print("X and y data : ", X ," y = ", y )
#print("yhat = ", yhat)
# report performance
rmse = sqrt(mean squared error(raw values[-15:], predictions))
print('Test RMSE: %.3f' % rmse)
# line plot of observed vs predicted
pyplot.plot(raw values[-15:])
pyplot.plot(predictions)
pyplot.show()
```

X.shape[1]), 1X.shape[2]) 1 875/875 [========== ] - 1s 2ms/step Month=1, Predicted=190.064803, Expected=188.590000 Month=2, Predicted=188.776842, Expected=188.150000 Month=3, Predicted=188.297215, Expected=186.440000 Month=4, Predicted=186.637043, Expected=188.180000 1/1 [======== ] - 0s 29ms/step Month=5, Predicted=188.241683, Expected=186.990000 Month=6, Predicted=187.166641, Expected=186.310000 Month=7, Predicted=186.466631, Expected=187.630000 Month=8, Predicted=187.708162, Expected=187.160000 1/1 [======= ] - Os 34ms/step Month=9, Predicted=187.308392, Expected=188.360000 1/1 [======= ] - 0s 34ms/step Month=10, Predicted=188.442870, Expected=188.150000 1/1 [======] - 0s 30ms/step Month=11, Predicted=188.288191, Expected=188.580000 1/1 [======= ] - Os 30ms/step Month=12, Predicted=188.693081, Expected=188.580000 1/1 [============= ] - 0s 31ms/step Month=13, Predicted=188.709952, Expected=187.900000 Month=14, Predicted=188.056631, Expected=187.500000 Month=15, Predicted=187.645645, Expected=186.870000 Test RMSE: 1.007



## **Bi-directional LSTM**

```
In [28]: raw_values = np.array(data_stock)
    diff_values = difference(raw_values, 1)
# modify data to be supervised
supervised = series_data_to_supervised_data(diff_values, 1)
supervised_values = supervised.values

# split data
train, test = supervised_values[0:-178], supervised_values[-178:]

# modify the scale of the data
scaler, train_scaled, test_scaled = scale(train, test)
```

```
# fit the model
bilstm model = fit bilstm(train scaled, 1, 1, 1)
# forecast
train reshaped = train scaled[:, 0].reshape(len(train scaled), 1, 1)
bilstm model.predict(train reshaped, batch size=1)
# walk-forward validation on the test data
predictions = list()
for i in range(len(test scaled)):
        # make one-step forecast
        X, y = test scaled[i, 0:-1], test scaled[i, -1]
        yhat = forecast bilstm(bilstm model, 1, X)
        # invert scaling
        yhat = invert scale(scaler, X, yhat)
        vhat = inverse the difference(raw values, vhat, len(test scaled)-i+1)
        # store forecast
        predictions.append(yhat)
        expected = raw values[len(train) + i + 1]
        print('Month=%d, Predicted=%f, Expected=%f' % (i+1, yhat, expected))
##print("X and y data: ", X ," y = ", y)
#print("yhat = ", yhat)
# report performance
rmse = sqrt(mean squared error(raw values[-178:], predictions))
print('\n Test RMSE: %.3f' % rmse)
# line plot of observed vs predicted
pyplot.plot(raw values[-178:])
pyplot.plot(predictions)
pyplot.show()
```

```
X.shape[1]), 1
X.shape[2]) 1
712/712 [========== ] - 2s 2ms/step
Month=1, Predicted=150.857409, Expected=153.140000
Month=2, Predicted=153.294014, Expected=154.230000
1/1 [======= ] - 0s 36ms/step
Month=3, Predicted=154.347763, Expected=153.280000
Month=4, Predicted=153.464256, Expected=154.120000
Month=5, Predicted=154.264055, Expected=153.810000
Month=6, Predicted=153.980908, Expected=154.480000
Month=7, Predicted=154.623137, Expected=153.480000
1/1 [======= ] - 0s 31ms/step
Month=8, Predicted=153.676675, Expected=155.390000
1/1 [======= ] - 0s 34ms/step
Month=9, Predicted=155.492840, Expected=155.300000
1/1 [======= ] - 0s 30ms/step
Month=10, Predicted=155.443962, Expected=155.840000
1/1 [======] - 0s 31ms/step
Month=11, Predicted=155.973014, Expected=155.900000
Month=12, Predicted=156.048947, Expected=156.550000
1/1 [======== ] - 0s 29ms/step
Month=13, Predicted=156.681157, Expected=156.000000
1/1 [======= ] - 0s 31ms/step
Month=14, Predicted=156.173226, Expected=156.990000
Month=15, Predicted=157.120026, Expected=159.880000
Month=16, Predicted=159.888880, Expected=160.470000
Month=17, Predicted=160.543346, Expected=159.760000
Month=18, Predicted=159.910294, Expected=155.980000
Month=19, Predicted=156.259854, Expected=156.250000
Month=20, Predicted=156.498853, Expected=156.170000
1/1 [======= ] - 0s 32ms/step
```

Month=21, Predicted=156.386530, Expected=157.100000 1/1 [======= ] - Os 37ms/step Month=22, Predicted=157.258985, Expected=156.410000 1/1 [======= ] - Os 29ms/step Month=23, Predicted=156.603077, Expected=157.410000 1/1 [======= ] - 0s 34ms/step Month=24, Predicted=157.552376, Expected=163.050000 Month=25, Predicted=162.902787, Expected=166.720000 Month=26, Predicted=166.564416, Expected=169.040000 1/1 [======== ] - 0s 30ms/step Month=27, Predicted=168.945421, Expected=166.890000 1/1 [======= ] - 0s 40ms/step Month=28, Predicted=167.034422, Expected=168.110000 Month=29, Predicted=168.208416, Expected=172.500000 Month=30, Predicted=172.400253, Expected=174.250000 Month=31, Predicted=174.220973, Expected=174.810000 1/1 [======= ] - 0s 31ms/step Month=32, Predicted=174.856552, Expected=176.240000 1/1 [======] - 0s 28ms/step Month=33, Predicted=176.273849, Expected=175.880000 Month=34, Predicted=175.998398, Expected=174.670000 1/1 [============= ] - 0s 31ms/step Month=35, Predicted=174.857930, Expected=173.970000 Month=36, Predicted=174.177477, Expected=171.340000 Month=37, Predicted=171.617155, Expected=169.080000 Month=38, Predicted=169.392377, Expected=171.100000 Month=39, Predicted=171.292491, Expected=170.150000 Month=40, Predicted=170.367778, Expected=169.980000 Month=41, Predicted=170.186188, Expected=173.140000 1/1 [======= ] - 0s 32ms/step Month=42, Predicted=173.184697, Expected=174.960000 1/1 [======= ] - 0s 31ms/step

Month=43, Predicted=174.988923, Expected=174.960000 1/1 [======= ] - Os 30ms/step Month=44, Predicted=175.064707, Expected=174.970000 1/1 [======= ] - Os 32ms/step Month=45, Predicted=175.104008, Expected=174.090000 Month=46, Predicted=174.275814, Expected=173.070000 Month=47, Predicted=173.288043, Expected=169.480000 Month=48, Predicted=169.785756, Expected=171.850000 1/1 [======== ] - 0s 30ms/step Month=49, Predicted=172.037224, Expected=171.050000 1/1 [======= ] - 0s 31ms/step Month=50, Predicted=171.259969, Expected=169.800000 1/1 [======= ] - Os 31ms/step Month=51, Predicted=170.039409, Expected=169.640000 Month=52, Predicted=169.859869, Expected=169.010000 Month=53, Predicted=169.232598, Expected=169.320000 1/1 [======= ] - 0s 36ms/step Month=54, Predicted=169.509856, Expected=169.370000 1/1 [======] - 0s 29ms/step Month=55, Predicted=169.550200, Expected=172.670000 1/1 [======= ] - 0s 31ms/step Month=56, Predicted=172.688598, Expected=171.700000 1/1 [============= ] - 0s 31ms/step Month=57, Predicted=171.850851, Expected=172.270000 1/1 [======= ] - Os 31ms/step Month=58, Predicted=172.404471, Expected=172.220000 Month=59, Predicted=172.374318, Expected=173.970000 Month=60, Predicted=174.052254, Expected=176.420000 1/1 [======= ] - 0s 31ms/step Month=61, Predicted=176.427225, Expected=174.540000 Month=62, Predicted=174.716400, Expected=174.350000 Month=63, Predicted=174.531984, Expected=175.010000 1/1 [======= ] - 0s 29ms/step Month=64, Predicted=175.159703, Expected=175.010000 1/1 [======= ] - 0s 31ms/step

Month=65, Predicted=175.170174, Expected=175.010000 1/1 [======= ] - Os 30ms/step Month=66, Predicted=175.175282, Expected=170.570000 1/1 [======= ] - Os 29ms/step Month=67, Predicted=170.870743, Expected=170.600000 1/1 [======= ] - 0s 34ms/step Month=68, Predicted=170.881010, Expected=171.080000 1/1 [======= ] - 0s 29ms/step Month=69, Predicted=171.294810, Expected=169.230000 Month=70, Predicted=169.488699, Expected=169.230000 1/1 [======== ] - 0s 33ms/step Month=71, Predicted=169.459085, Expected=172.260000 Month=72, Predicted=172.327214, Expected=172.230000 Month=73, Predicted=172.359743, Expected=173.030000 Month=74, Predicted=173.143125, Expected=175.000000 Month=75, Predicted=175.047658, Expected=174.350000 1/1 [======= ] - 0s 31ms/step Month=76, Predicted=174.492548, Expected=174.330000 1/1 [======] - 0s 34ms/step Month=77, Predicted=174.485196, Expected=174.290000 Month=78, Predicted=174.454049, Expected=175.280000 1/1 [======== ] - 0s 33ms/step Month=79, Predicted=175.404470, Expected=177.090000 Month=80, Predicted=177.152998, Expected=177.090000 1/1 [======= ] - Os 29ms/step Month=81, Predicted=177.210481, Expected=176.190000 1/1 [======= ] - 0s 29ms/step Month=82, Predicted=176.369682, Expected=179.100000 Month=83, Predicted=179.139579, Expected=179.260000 Month=84, Predicted=179.367320, Expected=178.460000 Month=85, Predicted=178.629350, Expected=177.000000 1/1 [======= ] - 0s 30ms/step Month=86, Predicted=177.223998, Expected=177.040000 

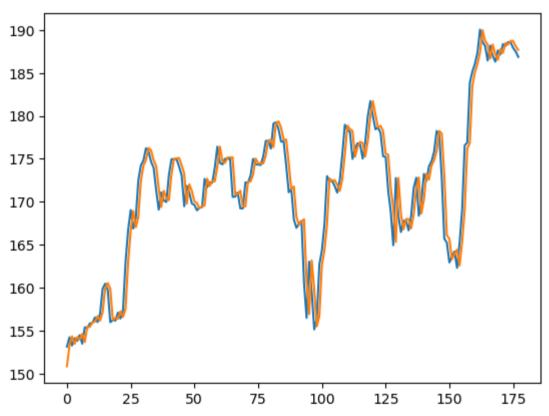
Month=87, Predicted=177.243153, Expected=174.220000 1/1 [======= ] - Os 30ms/step Month=88, Predicted=174.500069, Expected=171.110000 1/1 [======= ] - Os 30ms/step Month=89, Predicted=171.443784, Expected=171.510000 Month=90, Predicted=171.790146, Expected=167.960000 Month=91, Predicted=168.287831, Expected=166.970000 Month=92, Predicted=167.291957, Expected=167.430000 1/1 [======== ] - 0s 35ms/step Month=93, Predicted=167.677827, Expected=167.780000 1/1 [======= ] - 0s 31ms/step Month=94, Predicted=167.980007, Expected=160.500000 Month=95, Predicted=160.849476, Expected=156.490000 Month=96, Predicted=156.928884, Expected=163.030000 1/1 [======= ] - Os 29ms/step Month=97, Predicted=163.181504, Expected=159.540000 1/1 [======= ] - 0s 31ms/step Month=98, Predicted=159.818890, Expected=155.150000 1/1 [======] - 0s 32ms/step Month=99, Predicted=155.507983, Expected=156.410000 Month=100, Predicted=156.701788, Expected=162.710000 1/1 [======= ] - 0s 31ms/step Month=101, Predicted=162.633589, Expected=164.340000 1/1 [======= ] - 0s 30ms/step Month=102, Predicted=164.344390, Expected=167.370000 Month=103, Predicted=167.297394, Expected=172.990000 1/1 [======= ] - 0s 31ms/step Month=104, Predicted=172.712787, Expected=172.430000 1/1 [======= ] - 0s 32ms/step Month=105, Predicted=172.468535, Expected=172.430000 1/1 [======= ] - 0s 39ms/step Month=106, Predicted=172.522765, Expected=171.850000 1/1 [======= ] - 0s 29ms/step Month=107, Predicted=172.000477, Expected=171.070000 1/1 [======= ] - 0s 29ms/step Month=108, Predicted=171.258632, Expected=172.500000 1/1 [======= ] - 0s 29ms/step

Month=109, Predicted=172.619448, Expected=175.500000 1/1 [======= ] - 0s 30ms/step Month=110, Predicted=175.496652, Expected=178.970000 1/1 [======= ] - 0s 32ms/step Month=111, Predicted=178.875880, Expected=178.390000 1/1 [======= ] - 0s 30ms/step Month=112, Predicted=178.477982, Expected=178.120000 1/1 [======= ] - 0s 32ms/step Month=113, Predicted=178.253578, Expected=175.000000 Month=114, Predicted=175.255838, Expected=176.210000 1/1 [======= ] - 0s 31ms/step Month=115, Predicted=176.398309, Expected=176.820000 1/1 [======= ] - 0s 29ms/step Month=116, Predicted=176.974337, Expected=176.670000 Month=117, Predicted=176.838589, Expected=175.030000 Month=118, Predicted=175.259959, Expected=176.940000 1/1 [======] - 0s 34ms/step Month=119, Predicted=177.068683, Expected=179.980000 1/1 [======= ] - 0s 32ms/step Month=120, Predicted=179.981884, Expected=181.720000 1/1 [======= ] - 0s 30ms/step Month=121, Predicted=181.731142, Expected=179.970000 1/1 [======= ] - 0s 29ms/step Month=122, Predicted=180.139007, Expected=178.440000 1/1 [======= ] - 0s 30ms/step Month=123, Predicted=178.665813, Expected=178.650000 1/1 [======= ] - 0s 31ms/step Month=124, Predicted=178.847940, Expected=178.020000 1/1 [======= ] - 0s 31ms/step Month=125, Predicted=178.229799, Expected=175.300000 1/1 [======= ] - 0s 35ms/step Month=126, Predicted=175.581429, Expected=175.240000 1/1 [======= ] - 0s 33ms/step Month=127, Predicted=175.492423, Expected=171.270000 1/1 [======= ] - 0s 30ms/step Month=128, Predicted=171.595922, Expected=168.850000 1/1 [======= ] - 0s 31ms/step Month=129, Predicted=169.207736, Expected=164.940000 1/1 [======= ] - 0s 40ms/step Month=130, Predicted=165.324708, Expected=172.770000 1/1 [======= ] - 0s 29ms/step

```
Month=131, Predicted=172.780585, Expected=168.340000
1/1 [======] - 0s 31ms/step
Month=132, Predicted=168.610899, Expected=166.480000
1/1 [======= ] - 0s 30ms/step
Month=133, Predicted=166.790699, Expected=167.780000
1/1 [======= ] - 0s 31ms/step
Month=134, Predicted=167.996385, Expected=167.780000
1/1 [======= ] - 0s 33ms/step
Month=135, Predicted=167.974424, Expected=166.680000
Month=136, Predicted=166.905396, Expected=168.390000
1/1 [======= ] - 0s 30ms/step
Month=137, Predicted=168.522705, Expected=171.610000
1/1 [======= ] - 0s 31ms/step
Month=138, Predicted=171.604019, Expected=172.800000
Month=139, Predicted=172.838551, Expected=168.380000
1/1 [======= ] - 0s 36ms/step
Month=140, Predicted=168.638097, Expected=170.050000
1/1 [======= ] - 0s 29ms/step
Month=141, Predicted=170.230960, Expected=173.250000
1/1 [======= ] - 0s 29ms/step
Month=142, Predicted=173.273689, Expected=172.440000
Month=143, Predicted=172.584551, Expected=174.140000
1/1 [======= ] - 0s 33ms/step
Month=144, Predicted=174.217135, Expected=174.730000
1/1 [======= ] - 0s 31ms/step
Month=145, Predicted=174.829354, Expected=175.820000
1/1 [======= ] - 0s 30ms/step
Month=146, Predicted=175.902950, Expected=178.240000
1/1 [======= ] - 0s 29ms/step
Month=147, Predicted=178.245992, Expected=177.840000
1/1 [======= ] - 0s 32ms/step
Month=148, Predicted=177.954893, Expected=172.800000
1/1 [======= ] - 0s 32ms/step
Month=149, Predicted=173.091757, Expected=165.720000
1/1 [======= ] - 0s 30ms/step
Month=150, Predicted=166.113403, Expected=165.240000
Month=151, Predicted=165.675971, Expected=162.940000
1/1 [======] - 0s 35ms/step
Month=152, Predicted=163.317747, Expected=163.650000
1/1 [======= ] - 0s 29ms/step
```

Month=153, Predicted=163.942840, Expected=164.220000 1/1 [======] - 0s 31ms/step Month=154, Predicted=164.434906, Expected=162.320000 1/1 [======= ] - 0s 31ms/step Month=155, Predicted=162.580738, Expected=165.260000 1/1 [======= ] - 0s 30ms/step Month=156, Predicted=165.364548, Expected=169.100000 1/1 [======= ] - 0s 30ms/step Month=157, Predicted=169.045175, Expected=176.570000 Month=158, Predicted=176.180966, Expected=176.890000 1/1 [======= ] - 0s 33ms/step Month=159, Predicted=176.865097, Expected=183.830000 1/1 [======= ] - 0s 30ms/step Month=160, Predicted=183.460986, Expected=185.160000 Month=161, Predicted=185.071049, Expected=186.050000 1/1 [======= ] - 0s 31ms/step Month=162, Predicted=186.042804, Expected=187.360000 1/1 [======] - 0s 32ms/step Month=163, Predicted=187.369960, Expected=190.040000 1/1 [======= ] - 0s 33ms/step Month=164, Predicted=189.986419, Expected=188.590000 1/1 [======= ] - 0s 35ms/step Month=165, Predicted=188.722281, Expected=188.150000 1/1 [======= ] - 0s 30ms/step Month=166, Predicted=188.313389, Expected=186.440000 1/1 [======= ] - 0s 30ms/step Month=167, Predicted=186.667396, Expected=188.180000 1/1 [======= ] - 0s 33ms/step Month=168, Predicted=188.315112, Expected=186.990000 Month=169, Predicted=187.189592, Expected=186.310000 1/1 [======= ] - 0s 29ms/step Month=170, Predicted=186.523953, Expected=187.630000 1/1 [======= ] - 0s 29ms/step Month=171, Predicted=187.771310, Expected=187.160000 1/1 [======= ] - 0s 31ms/step Month=172, Predicted=187.335930, Expected=188.360000 Month=173, Predicted=188.482099, Expected=188.150000 1/1 [======= ] - 0s 31ms/step Month=174, Predicted=188.306083, Expected=188.580000 1/1 [======= ] - 0s 31ms/step

Test RMSE: 2.392



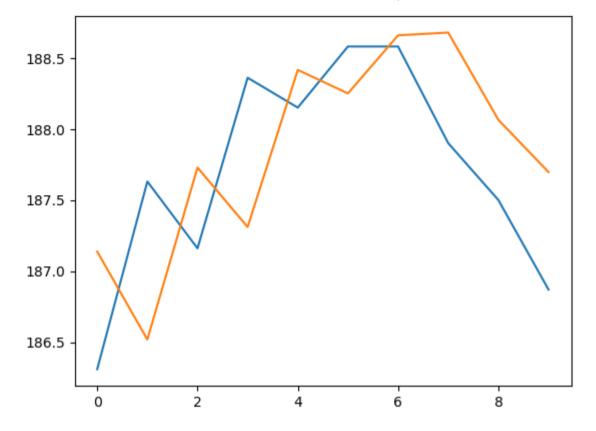
### Over 15 test rows

```
In [29]: raw_values = np.array(data_stock)
    diff_values = difference(raw_values, 1)
    # modify data to be supervised
    supervised = series_data_to_supervised_data(diff_values, 1)
```

```
supervised values = supervised.values
# split data
train, test = supervised values[0:-10], supervised values[-10:]
# modify the scale of the data
scaler, train scaled, test scaled = scale(train, test)
# fit the model
bilstm model = fit bilstm(train scaled, 1, 1, 1)
# forecast
train reshaped = train scaled[:, 0].reshape(len(train scaled), 1, 1)
bilstm model.predict(train reshaped, batch size=1)
# walk-forward validation on the test data
predictions = list()
for i in range(len(test scaled)):
       # make one-step forecast
       X, y = test scaled[i, 0:-1], test scaled[i, -1]
       yhat = forecast bilstm(bilstm model, 1, X)
        # invert scaling
        vhat = invert scale(scaler, X, yhat)
        yhat = inverse the difference(raw values, yhat, len(test scaled)-i+1)
        # store forecast
        predictions.append(yhat)
        expected = raw values[len(train) + i + 1]
        print('Month=%d, Predicted=%f, Expected=%f' % (i+1, yhat, expected))
##print("X and y data : ", X ," y = ", y )
#print("yhat = ", yhat)
# report performance
rmse = sqrt(mean squared_error(raw_values[-10:], predictions))
print('\n Test RMSE: %.3f' % rmse)
# line plot of observed vs predicted
pyplot.plot(raw values[-10:])
pyplot.plot(predictions)
pyplot.show()
```

```
X.shape[1]), 1
X.shape[2]) 1
880/880 [========== ] - 3s 2ms/step
1/1 [======= ] - Os 29ms/step
Month=1, Predicted=187.137314, Expected=186.310000
Month=2, Predicted=186.518677, Expected=187.630000
Month=3, Predicted=187.728263, Expected=187.160000
Month=4, Predicted=187.309943, Expected=188.360000
1/1 [======] - 0s 30ms/step
Month=5, Predicted=188.415160, Expected=188.150000
Month=6, Predicted=188.249773, Expected=188.580000
Month=7, Predicted=188.658451, Expected=188.580000
1/1 [======= ] - 0s 31ms/step
Month=8, Predicted=188.678007, Expected=187.900000
Month=9, Predicted=188.064169, Expected=187.500000
Month=10, Predicted=187.696476, Expected=186.870000
```

Test RMSE: 0.717



# **Arima Model**

In [30]: pip install statsmodels

```
Requirement already satisfied: statsmodels in c:\users\jaypa\anaconda3\lib\site-packages (0.13.2)
         Requirement already satisfied: numpy>=1.17 in c:\users\jaypa\anaconda3\lib\site-packages (from statsmodels) (1.22.4)
         Requirement already satisfied: scipy>=1.3 in c:\users\jaypa\anaconda3\lib\site-packages (from statsmodels) (1.9.1)
         Requirement already satisfied: pandas>=0.25 in c:\users\jaypa\anaconda3\lib\site-packages (from statsmodels) (1.4.4)
         Requirement already satisfied: patsy>=0.5.2 in c:\users\jaypa\anaconda3\lib\site-packages (from statsmodels) (0.5.2)
         Requirement already satisfied: packaging>=21.3 in c:\users\jaypa\anaconda3\lib\site-packages (from statsmodels) (21.3)
         Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in c:\users\jaypa\anaconda3\lib\site-packages (from packaging>=21.3->sta
         tsmodels) (3.0.9)
         Requirement already satisfied: pytz>=2020.1 in c:\users\jaypa\anaconda3\lib\site-packages (from pandas>=0.25->statsmodels) (202
         2.1)
         Requirement already satisfied: python-dateutil>=2.8.1 in c:\users\jaypa\anaconda3\lib\site-packages (from pandas>=0.25->statsmod
         els) (2.8.2)
         Requirement already satisfied: six in c:\users\jaypa\anaconda3\lib\site-packages (from patsy>=0.5.2->statsmodels) (1.16.0)
         Note: you may need to restart the kernel to use updated packages.
In [31]: import numpy as np
          data stock np = np.array(data stock)
In [32]: from statsmodels.tsa.arima.model import ARIMA
          import statsmodels.api as sm
          import numpy as np
          from matplotlib import pyplot
          #data = data[['Date']]
          data = np.asarray(data stock np)
In [33]: model = ARIMA(data, order=(5,1,5))
          model fit = model.fit()
          # summary of fit model
          print(model fit.summary())
          # line plot of residuals
          residuals = pd.DataFrame(model fit.resid)
          residuals.plot()
          pyplot.show()
          # density plot of residuals
          residuals.plot(kind='kde')
          pyplot.show()
          # summary stats of residuals
          print(residuals.describe())
```

C:\Users\jaypa\anaconda3\lib\site-packages\statsmodels\base\model.py:604: ConvergenceWarning: Maximum Likelihood optimization fa
iled to converge. Check mle\_retvals

warnings.warn("Maximum Likelihood optimization failed to "

#### SARIMAX Results

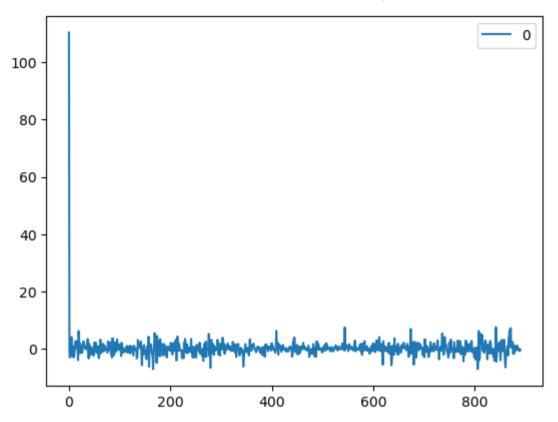
============			
Dep. Variable:	у	No. Observations:	891
Model:	ARIMA(5, 1, 5)	Log Likelihood	-1798.906
Date:	Fri, 15 Dec 2023	AIC	3619.812
Time:	21:27:53	BIC	3672.515
Sample:	0	HQIC	3639.955

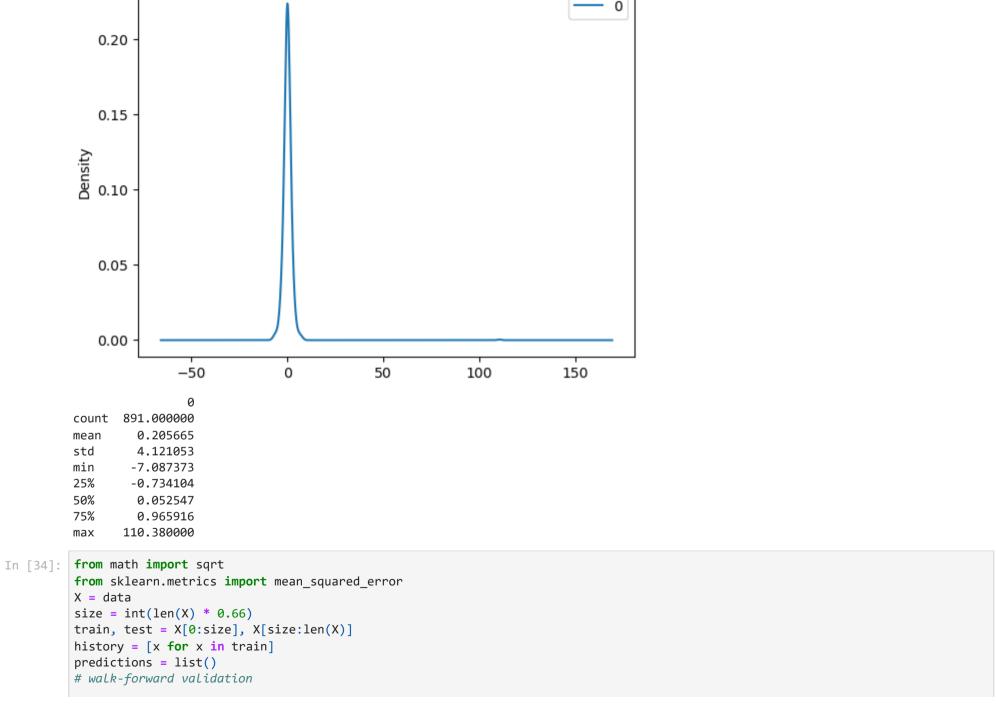
- 891 Covariance Type: opg

.,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,		- 10				
=======	coef	std err	======= Z	P> z	[0.025	0.975]
	4 2004		4 000		0.600	
ar.L1	-1.3001	0.683	-1.903	0.057	-2.639	0.039
ar.L2	-0.8280	1.516	-0.546	0.585	-3.800	2.144
ar.L3	0.5055	1.932	0.262	0.794	-3.282	4.293
ar.L4	0.8613	1.358	0.634	0.526	-1.801	3.524
ar.L5	0.7209	0.574	1.257	0.209	-0.404	1.845
ma.L1	1.3449	0.687	1.957	0.050	-0.002	2.692
ma.L2	0.8590	1.558	0.551	0.581	-2.194	3.912
ma.L3	-0.5324	1.999	-0.266	0.790	-4.451	3.386
ma.L4	-0.8748	1.394	-0.627	0.530	-3.607	1.858
ma.L5	-0.7011	0.578	-1.213	0.225	-1.834	0.432
sigma2	3.3431	0.111	30.180	0.000	3.126	3.560
======================================		 0.46			 236.4	
Prob(Q):		0.50	Prob(JB):		0.0	
Heteroskedasticity (H):			1.18	Skew:		0.0
Prob(H) (two-sided):			0.15	Kurtosis:		5.5

#### Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).





```
for t in range(len(test)):
        model = ARIMA(history, order=(5,1,0))
        model fit = model.fit()
        output = model fit.forecast()
        yhat = output[0]
        predictions.append(yhat)
        obs = test[t]
        history.append(obs)
        print('predicted=%f, expected=%f' % (yhat, obs))
# evaluate forecasts
rmse = sqrt(mean_squared_error(test, predictions))
print('Test RMSE: %.3f' % rmse)
# plot forecasts against actual outcomes
pyplot.plot(test)
pyplot.plot(predictions, color='red')
pyplot.show()
```

```
predicted=143.608176, expected=144.770000
predicted=144.784362, expected=144.020000
predicted=143.977548, expected=143.660000
predicted=143.644291, expected=143.340000
predicted=143.377365, expected=143.170000
predicted=143.160002, expected=141.630000
predicted=141.657881, expected=141.800000
predicted=141.878979, expected=141.050000
predicted=141.114360, expected=141.050000
predicted=141.078864, expected=141.830000
predicted=141.928846, expected=141.200000
predicted=141.160754, expected=140.680000
predicted=140.688279, expected=142.440000
predicted=142.505570, expected=142.270000
predicted=142.200036, expected=143.640000
predicted=143.610734, expected=144.530000
predicted=144.512529, expected=143.680000
predicted=143.517691, expected=143.790000
predicted=143.783120, expected=143.650000
predicted=143.626870, expected=146.580000
predicted=146.588935, expected=147.510000
predicted=147.453348, expected=147.060000
predicted=146.890607, expected=146.530000
predicted=146.490825, expected=148.960000
predicted=148.934495, expected=153.010000
predicted=152.993657, expected=153.990000
predicted=153.768625, expected=153.260000
predicted=153.048311, expected=153.950000
predicted=153.905016, expected=156.100000
predicted=156.071392, expected=155.700000
predicted=155.553400, expected=155.470000
predicted=155.415367, expected=150.250000
predicted=150.164348, expected=152.540000
predicted=152.728483, expected=153.060000
predicted=153.238782, expected=153.990000
predicted=153.823913, expected=153.800000
predicted=153.861755, expected=153.340000
predicted=153.256333, expected=153.870000
predicted=153.904007, expected=153.610000
predicted=153.591962, expected=153.610000
predicted=153.592076, expected=153.670000
predicted=153.696654, expected=152.760000
predicted=152.732906, expected=153.180000
predicted=153.220893, expected=155.450000
```

```
predicted=155.514709, expected=153.930000
predicted=153.793858, expected=154.450000
predicted=154.421143, expected=155.370000
predicted=155.446025, expected=154.990000
predicted=154.873265, expected=148.980000
predicted=148.910361, expected=145.420000
predicted=145.591930, expected=146.590000
predicted=147.055563, expected=145.160000
predicted=145.168058, expected=144.290000
predicted=144.359509, expected=142.270000
predicted=142.397389, expected=146.340000
predicted=146.487528, expected=145.010000
predicted=144.937566, expected=145.870000
predicted=145.711761, expected=145.630000
predicted=145.806805, expected=146.280000
predicted=146.117969, expected=145.820000
predicted=145.857524, expected=143.730000
predicted=143.652456, expected=145.830000
predicted=145.983037, expected=143.680000
predicted=143.653894, expected=144.020000
predicted=143.962008, expected=143.500000
predicted=143.684130, expected=143.500000
predicted=143.403557, expected=144.090000
predicted=144.177328, expected=142.730000
predicted=142.676737, expected=144.180000
predicted=144.222570, expected=145.060000
predicted=145.095783, expected=145.530000
predicted=145.394309, expected=145.740000
predicted=145.743037, expected=147.770000
predicted=147.751484, expected=149.040000
predicted=148.970783, expected=149.560000
predicted=149.426942, expected=150.080000
predicted=150.056443, expected=151.020000
predicted=150.982990, expected=150.340000
predicted=150.263560, expected=150.270000
predicted=150.250632, expected=152.090000
predicted=152.158403, expected=152.740000
predicted=152.655729, expected=153.460000
predicted=153.380697, expected=150.560000
predicted=150.516177, expected=149.500000
predicted=149.529135, expected=148.730000
predicted=148.894920, expected=150.050000
predicted=150.061674, expected=157.140000
predicted=157.298472, expected=155.570000
```

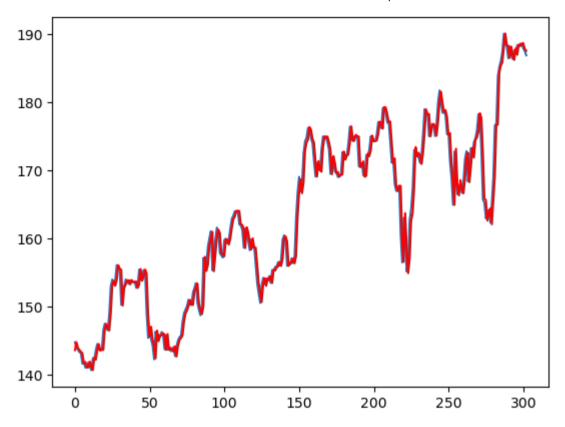
```
predicted=155.223972, expected=156.390000
predicted=156.113198, expected=158.810000
predicted=158.964885, expected=160.080000
predicted=159.844606, expected=161.060000
predicted=160.962914, expected=155.320000
predicted=155.190061, expected=157.480000
predicted=157.657067, expected=159.850000
predicted=160.060587, expected=161.600000
predicted=161.292528, expected=160.950000
predicted=160.808186, expected=157.860000
predicted=157.822865, expected=157.500000
predicted=157.709911, expected=157.210000
predicted=157.389418, expected=159.780000
predicted=159.779478, expected=159.980000
predicted=159.860220, expected=159.270000
predicted=159.097755, expected=159.860000
predicted=159.924039, expected=161.470000
predicted=161.526823, expected=162.910000
predicted=162.812421, expected=163.350000
predicted=163.206146, expected=164.000000
predicted=163.944490, expected=164.050000
predicted=164.042793, expected=164.050000
predicted=164.034563, expected=162.080000
predicted=162.070361, expected=161.910000
predicted=161.996565, expected=161.260000
predicted=161.372041, expected=158.630000
predicted=158.595545, expected=161.500000
predicted=161.650501, expected=160.860000
predicted=160.870034, expected=159.650000
predicted=159.468123, expected=158.280000
predicted=158.377098, expected=159.880000
predicted=160.028153, expected=158.670000
predicted=158.641016, expected=158.730000
predicted=158.659503, expected=156.070000
predicted=156.142117, expected=153.390000
predicted=153.457393, expected=151.890000
predicted=152.110045, expected=150.550000
predicted=150.671360, expected=153.140000
predicted=153.233350, expected=154.230000
predicted=154.173851, expected=153.280000
predicted=153.043985, expected=154.120000
predicted=154.138635, expected=153.810000
predicted=153.864596, expected=154.480000
predicted=154.448764, expected=153.480000
```

```
predicted=153.465203, expected=155.390000
predicted=155.412248, expected=155.300000
predicted=155.291327, expected=155.840000
predicted=155.729683, expected=155.900000
predicted=155.910698, expected=156.550000
predicted=156.537241, expected=156.000000
predicted=155.975711, expected=156.990000
predicted=156.988816, expected=159.880000
predicted=159.918674, expected=160.470000
predicted=160.308911, expected=159.760000
predicted=159.582725, expected=155.980000
predicted=155.980134, expected=156.250000
predicted=156.479871, expected=156.170000
predicted=156.378974, expected=157.100000
predicted=157.027632, expected=156.410000
predicted=156.343657, expected=157.410000
predicted=157.391133, expected=163.050000
predicted=163.150562, expected=166.720000
predicted=166.524634, expected=169.040000
predicted=168.673134, expected=166.890000
predicted=166.635780, expected=168.110000
predicted=168.208157, expected=172.500000
predicted=172.845619, expected=174.250000
predicted=174.062989, expected=174.810000
predicted=174.504634, expected=176.240000
predicted=176.342418, expected=175.880000
predicted=175.942899, expected=174.670000
predicted=174.617099, expected=173.970000
predicted=174.061660, expected=171.340000
predicted=171.356851, expected=169.080000
predicted=169.078673, expected=171.100000
predicted=171.347921, expected=170.150000
predicted=170.083702, expected=169.980000
predicted=169.792521, expected=173.140000
predicted=173.315315, expected=174.960000
predicted=174.918953, expected=174.960000
predicted=174.723959, expected=174.970000
predicted=174.961691, expected=174.090000
predicted=174.140242, expected=173.070000
predicted=173.082228, expected=169.480000
predicted=169.424716, expected=171.850000
predicted=172.085613, expected=171.050000
predicted=171.095977, expected=169.800000
predicted=169.574254, expected=169.640000
```

```
predicted=169.748975, expected=169.010000
predicted=169.056409, expected=169.320000
predicted=169.322226, expected=169.370000
predicted=169.376246, expected=172.670000
predicted=172.745127, expected=171.700000
predicted=171.558394, expected=172.270000
predicted=172.159592, expected=172.220000
predicted=172.327775, expected=173.970000
predicted=173.994698, expected=176.420000
predicted=176.450407, expected=174.540000
predicted=174.318845, expected=174.350000
predicted=174.329806, expected=175.010000
predicted=175.210343, expected=175.010000
predicted=174.977154, expected=175.010000
predicted=174.951830, expected=170.570000
predicted=170.448733, expected=170.600000
predicted=170.761967, expected=171.080000
predicted=171.313344, expected=169.230000
predicted=169.044262, expected=169.230000
predicted=169.205224, expected=172.260000
predicted=172.446143, expected=172.230000
predicted=172.073558, expected=173.030000
predicted=172.901721, expected=175.000000
predicted=175.105550, expected=174.350000
predicted=174.247722, expected=174.330000
predicted=174.289005, expected=174.290000
predicted=174.368797, expected=175.280000
predicted=175.312432, expected=177.090000
predicted=177.103726, expected=177.090000
predicted=176.980840, expected=176.190000
predicted=176.108623, expected=179.100000
predicted=179.273490, expected=179.260000
predicted=179.210073, expected=178.460000
predicted=178.292349, expected=177.000000
predicted=177.045540, expected=177.040000
predicted=177.160714, expected=174.220000
predicted=174.174416, expected=171.110000
predicted=171.064688, expected=171.510000
predicted=171.741778, expected=167.960000
predicted=167.865063, expected=166.970000
predicted=166.932906, expected=167.430000
predicted=167.582725, expected=167.780000
predicted=167.718477, expected=160.500000
predicted=160.176407, expected=156.490000
```

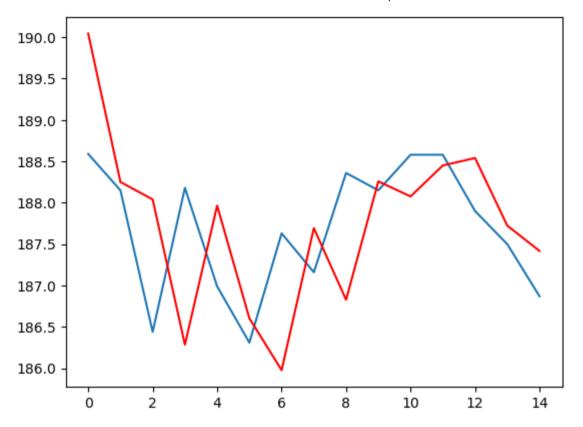
```
predicted=156.565135, expected=163.030000
predicted=163.706095, expected=159.540000
predicted=158.937960, expected=155.150000
predicted=154.902993, expected=156.410000
predicted=157.028934, expected=162.710000
predicted=162.616797, expected=164.340000
predicted=163.693683, expected=167.370000
predicted=167.388306, expected=172.990000
predicted=173.401282, expected=172.430000
predicted=172.037684, expected=172.430000
predicted=172.581878, expected=171.850000
predicted=172.073463, expected=171.070000
predicted=170.930845, expected=172.500000
predicted=172.617247, expected=175.500000
predicted=175.522977, expected=178.970000
predicted=178.929378, expected=178.390000
predicted=178.231151, expected=178.120000
predicted=178.247289, expected=175.000000
predicted=174.979272, expected=176.210000
predicted=176.357550, expected=176.820000
predicted=176.808474, expected=176.670000
predicted=176.468943, expected=175.030000
predicted=175.068518, expected=176.940000
predicted=177.131069, expected=179.980000
predicted=180.009557, expected=181.720000
predicted=181.523586, expected=179.970000
predicted=179.870471, expected=178.440000
predicted=178.571190, expected=178.650000
predicted=178.818452, expected=178.020000
predicted=177.878024, expected=175.300000
predicted=175.152800, expected=175.240000
predicted=175.451087, expected=171.270000
predicted=171.071466, expected=168.850000
predicted=168.813734, expected=164.940000
predicted=164.920258, expected=172.770000
predicted=173.170128, expected=168.340000
predicted=167.830634, expected=166.480000
predicted=166.317813, expected=167.780000
predicted=168.565124, expected=167.780000
predicted=167.291035, expected=166.680000
predicted=166.618044, expected=168.390000
predicted=168.633016, expected=171.610000
predicted=171.596896, expected=172.800000
predicted=172.575615, expected=168.380000
```

predicted=168.257332, expected=170.050000 predicted=170.512532, expected=173.250000 predicted=173.285095, expected=172.440000 predicted=171.863264, expected=174.140000 predicted=174.443163, expected=174.730000 predicted=174.807786, expected=175.820000 predicted=175.669052, expected=178.240000 predicted=178.376362, expected=177.840000 predicted=177.671460, expected=172.800000 predicted=172.696843, expected=165.720000 predicted=165.849475, expected=165.240000 predicted=165.639208, expected=162.940000 predicted=162.622756, expected=163.650000 predicted=163.560757, expected=164.220000 predicted=164.431583, expected=162.320000 predicted=162.074659, expected=165.260000 predicted=165.596173, expected=169.100000 predicted=169.127261, expected=176.570000 predicted=176.627510, expected=176.890000 predicted=176.693903, expected=183.830000 predicted=184.347149, expected=185.160000 predicted=185.366108, expected=186.050000 predicted=185.830058, expected=187.360000 predicted=187.876054, expected=190.040000 predicted=190.065010, expected=188.590000 predicted=188.440431, expected=188.150000 predicted=188.244308, expected=186.440000 predicted=186.500263, expected=188.180000 predicted=188.147654, expected=186.990000 predicted=186.880177, expected=186.310000 predicted=186.195659, expected=187.630000 predicted=187.911454, expected=187.160000 predicted=186.946631, expected=188.360000 predicted=188.434007, expected=188.150000 predicted=188.215764, expected=188.580000 predicted=188.537432, expected=188.580000 predicted=188.667736, expected=187.900000 predicted=187.808694, expected=187.500000 predicted=187.535881, expected=186.870000 Test RMSE: 2.146

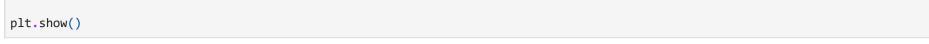


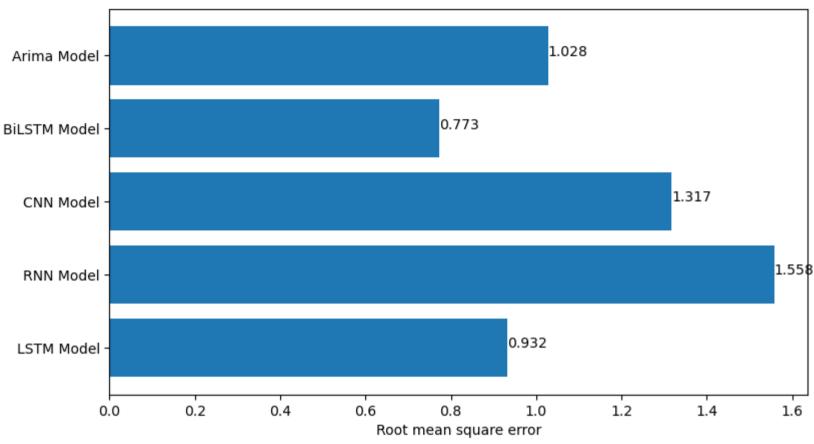
```
In [35]: from math import sqrt
         from sklearn.metrics import mean squared error
         X = data
         size = 876
         train, test = X[0:size], X[size:len(X)]
         history = [x for x in train]
         predictions = list()
         # walk-forward validation
         for t in range(len(test)):
                 model = ARIMA(history, order=(5,1,1))
                 model fit = model.fit()
                 output = model_fit.forecast()
                 yhat = output[0]
                 predictions.append(yhat)
                 obs = test[t]
                 history.append(obs)
                  print('predicted=%f, expected=%f' % (yhat, obs))
```

```
# evaluate forecasts
rmse = sqrt(mean squared error(test, predictions))
print('Test RMSE: %.3f' % rmse)
# plot forecasts against actual outcomes
pyplot.plot(test)
pyplot.plot(predictions, color='red')
pyplot.show()
predicted=190.044783, expected=188.590000
predicted=188.250956, expected=188.150000
predicted=188.039589, expected=186.440000
predicted=186.285071, expected=188.180000
predicted=187.965689, expected=186.990000
predicted=186.603641, expected=186.310000
predicted=185.976972, expected=187.630000
predicted=187.693149, expected=187.160000
predicted=186.828252, expected=188.360000
predicted=188.257974, expected=188.150000
predicted=188.076107, expected=188.580000
predicted=188.450625, expected=188.580000
predicted=188.540922, expected=187.900000
predicted=187.723895, expected=187.500000
predicted=187.417436, expected=186.870000
Test RMSE: 1.024
```



# Make results for comparision





## **References:**

[1]: R. Khandelwal, P. Marfatia, S. Shah, V. Joshi, P. Kamath and K. Chavan, "Financial Data Time Series Forecasting Using Neural Networks and a Comparative Study," 2022 International Conference for Advancement in Technology (ICONAT), Goa, India, 2022, pp. 1-6, doi: 10.1109/ICONAT53423.2022.9725845.

[2]: R. Khandelwal (2022, January 28). Financial-Data-Time-Series-Forecasting-Using-Neural-Networks. https://github.com/ritvik02/Financial-Data-Time-Series-Forecasting-Using-Neural-Networks

**Research Paper Link:** https://github.com/ritvik02/Financial-Data-Time-Series-Forecasting-Using-Neural-Networks/blob/main/Paper.pdf

**Source Link:** https://ieeexplore.ieee.org/document/9725845

In [ ]: