

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/
```

```
In [2]: data.head()
```

```
Out[2]:
```

	Unnamed: 0	A	AAL	AAP	AAPL	ABBV	ABC	ABMD	ABT	ACN	...	XLNX	XOM	XRAY	XRX	XYL	YUM	ZBH	ZION	ZTS
0	01/01/2015	40.94	53.630	159.28	110.38	65.44	90.16	38.06	45.02	89.31	...	43.290	92.45	53.27	36.5155	38.07	52.3831	113.42	28.510	43.03
1	02/01/2015	40.56	53.910	158.56	109.33	65.89	90.46	37.31	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	27.230	43.05
3	06/01/2015	39.18	53.040	156.36	106.26	64.33	90.18	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 rows × 507 columns

```
In [3]: data.columns
```

```
Out[3]: Index(['Unnamed: 0', 'A ', 'AAL ', 'AAP ', 'AAPL ', 'ABBV ', 'ABC ', 'ABMD ',
            'ABT ', 'ACN ',
            ...,
            'XLNX ', 'XOM ', 'XRAY ', 'XRX ', 'XYL ', 'YUM ', 'ZBH ', 'ZION ',
            'ZTS ', 'Cash'],
            dtype='object', length=507)
```

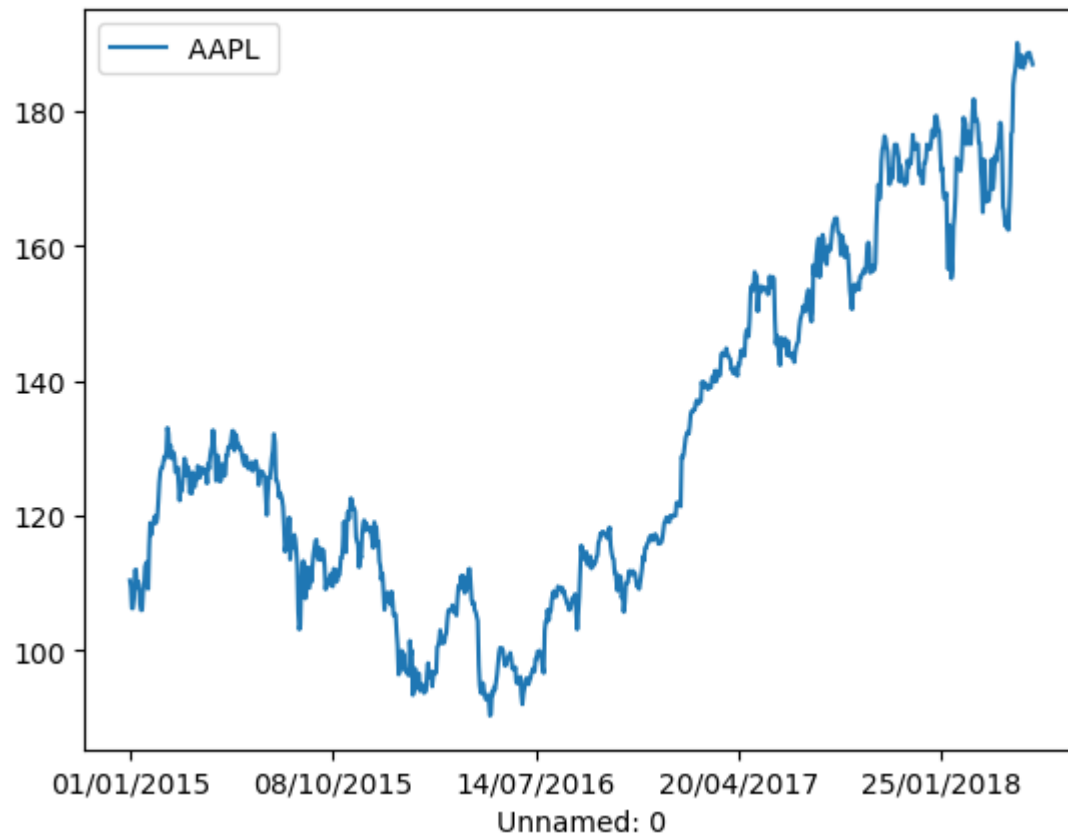
```
In [4]: # sum of null values in the data  
data.isna().sum()
```

```
Out[4]: Unnamed: 0      0  
A          0  
AAL        0  
AAP        0  
AAPL       0  
          ..  
YUM        0  
ZBH        0  
ZION       0  
ZTS        0  
Cash       0  
Length: 507, dtype: int64
```

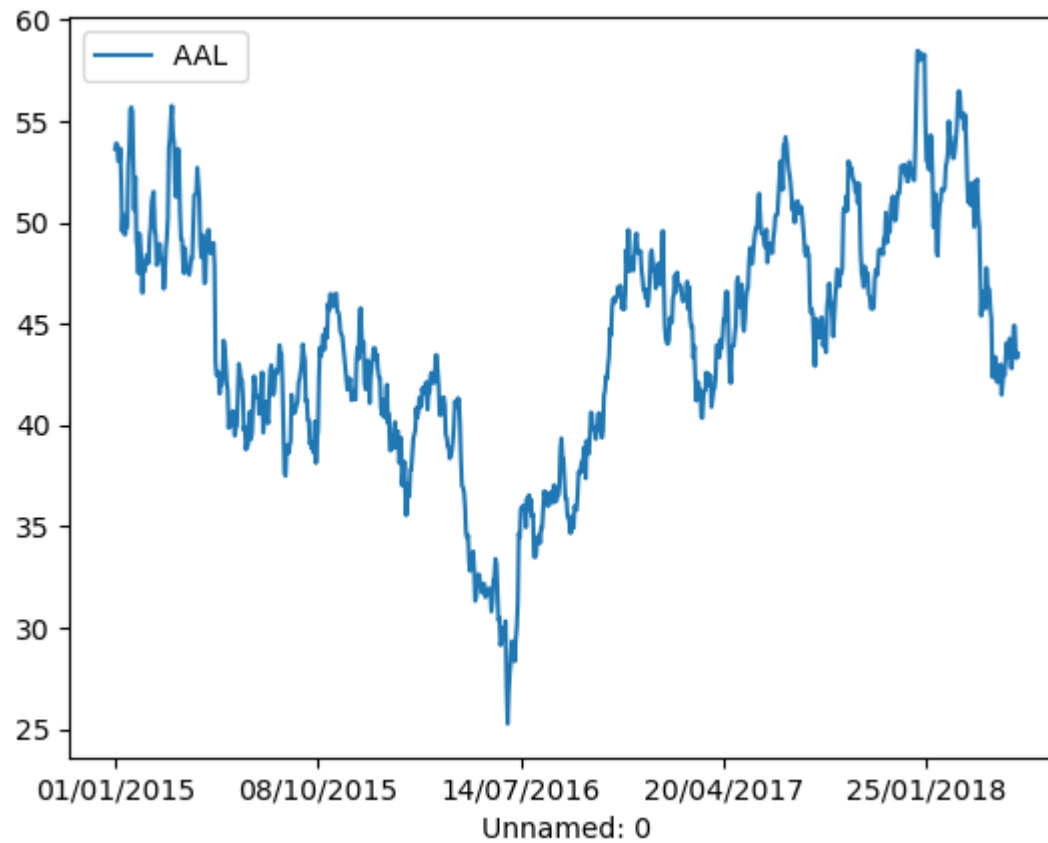
```
In [5]: # # converting date column from object to datetime  
# data['Unnamed: 0'] = pd.to_datetime(data['Unnamed: 0'])
```

Trend Analysis

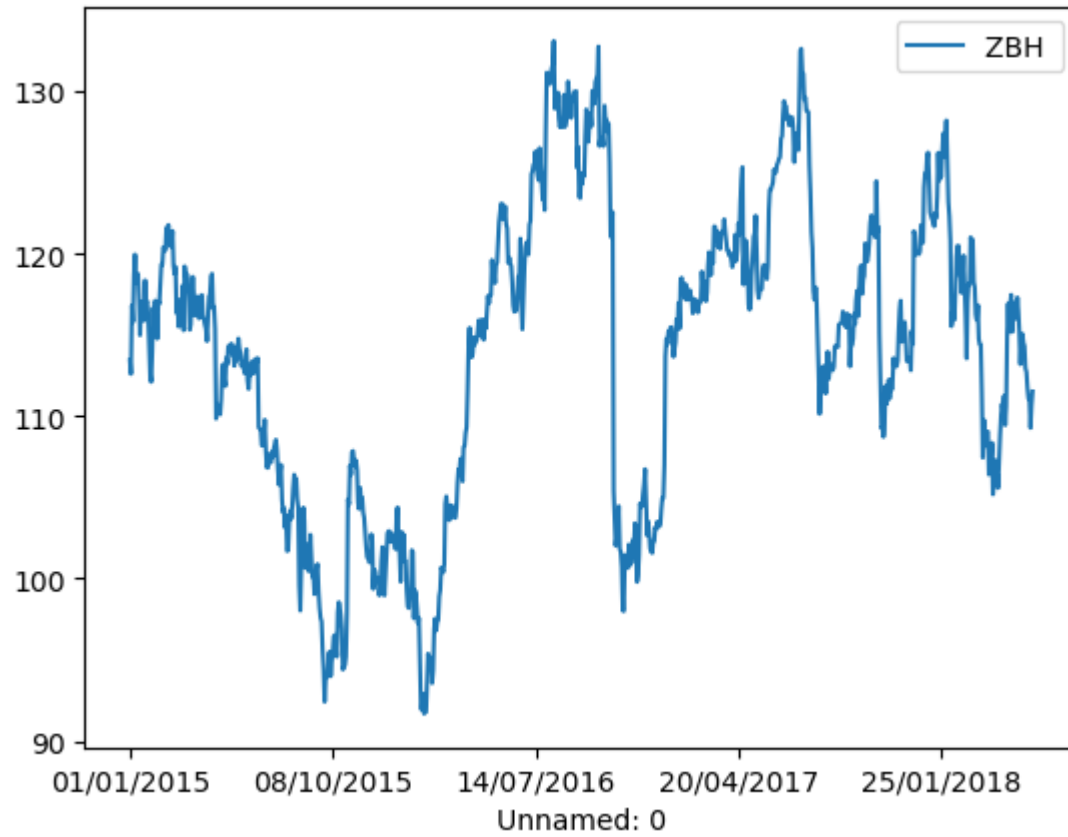
```
In [6]: import matplotlib.pyplot as plt  
  
# using matplotlib to plot the data  
data.plot.line(x = 'Unnamed: 0', y = 'AAPL ')  
plt.show()
```



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



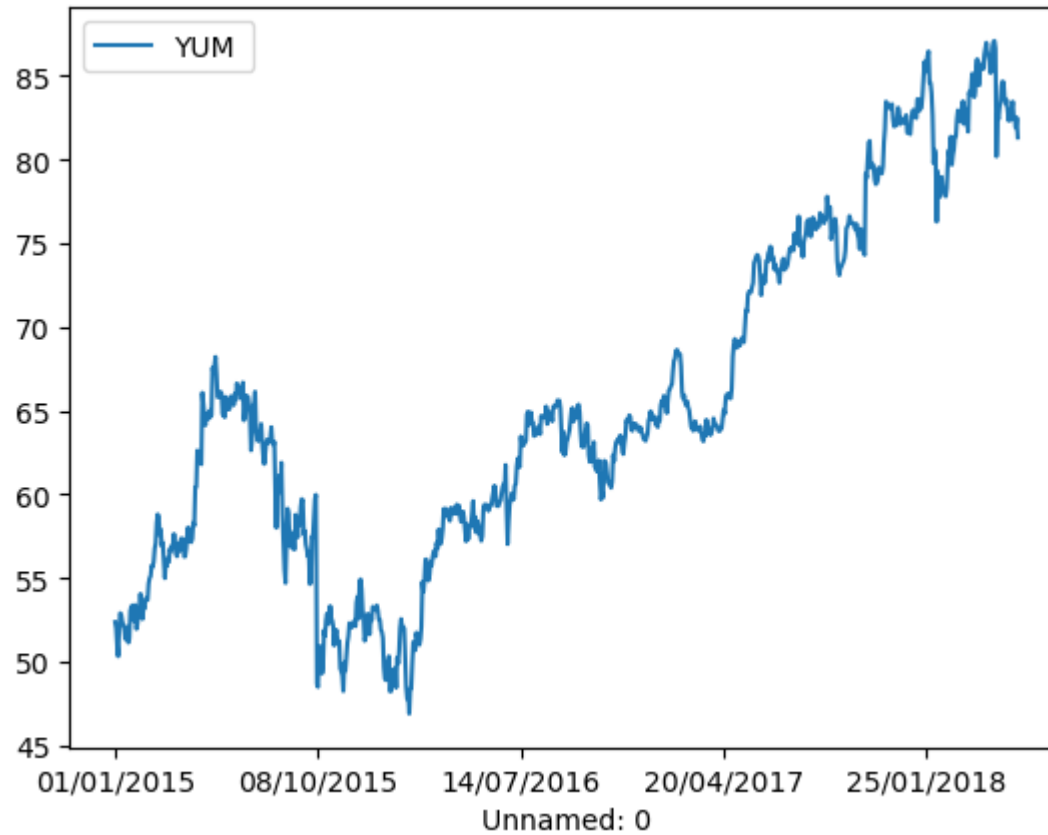
```
In [8]: # using matplotlib to plot the data
data.plot.line(x = 'Unnamed: 0', y = 'ZBH ')
plt.show()
```



```
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
```

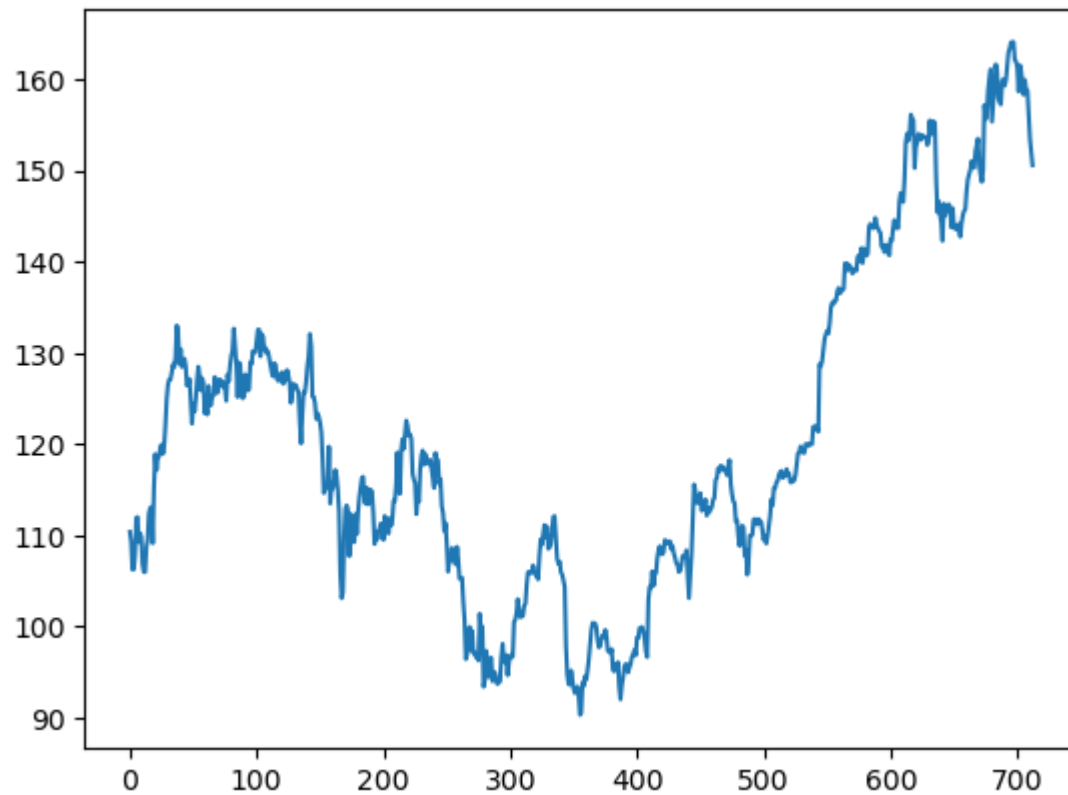
```
Out[13]: 713
```

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

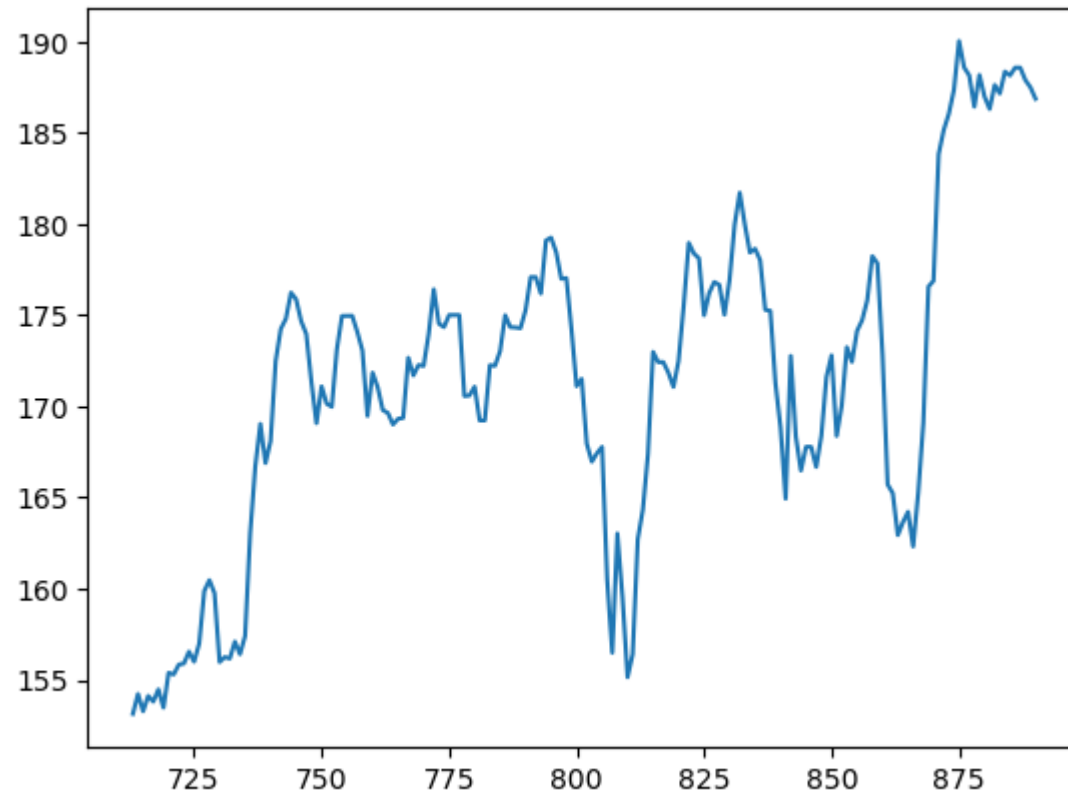
```
In [15]: data_stock_np[-15]
```

```
Out[15]: 188.59
```

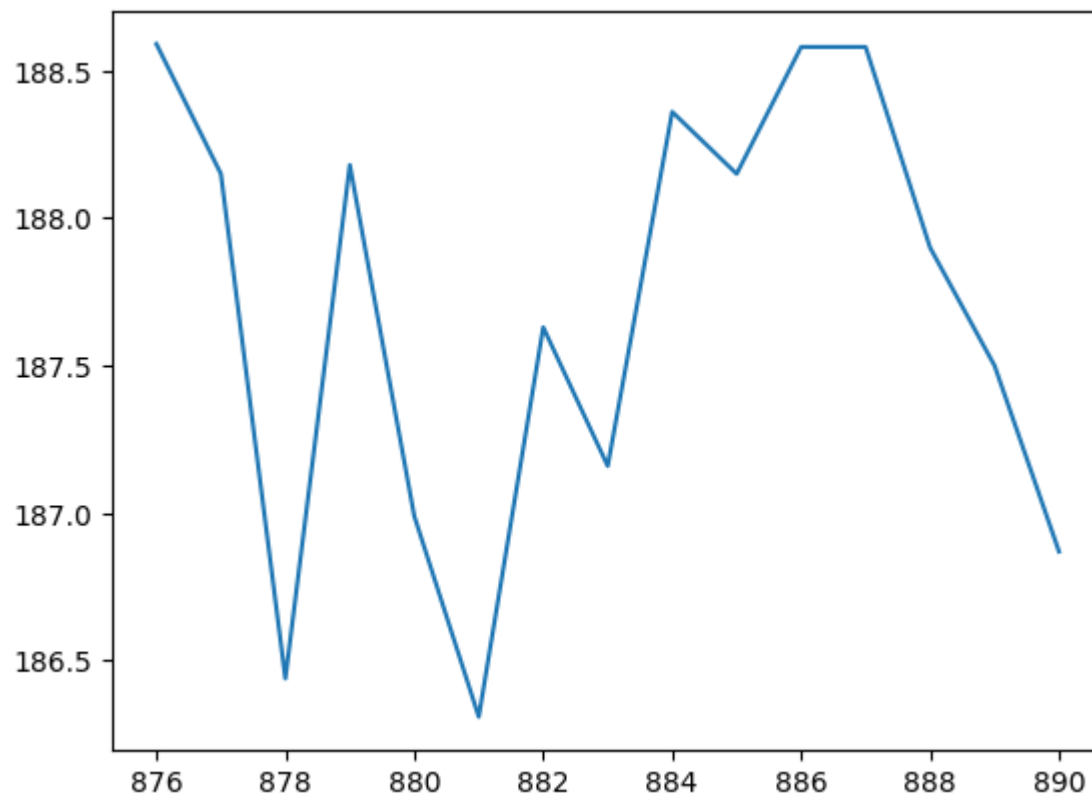
```
In [16]: data_stock[:713].plot.line(x = 'Unnamed: 0', y = 'AAPL ')  
plt.show()
```



```
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 ')\nplt.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 for x 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 yhat[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 yhat[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 yhat[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]: 178.20000000000002

```

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_resaped = train_scaled[:, 0].reshape(len(train_scaled), 1, 1)
lstm_model.predict(train_resaped, 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)

    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()
```

712/712 [=====] - 2s 2ms/step

1/1 [=====] - 0s 29ms/step

1/1 [=====] - 0s 33ms/step

1/1 [=====] - 0s 33ms/step

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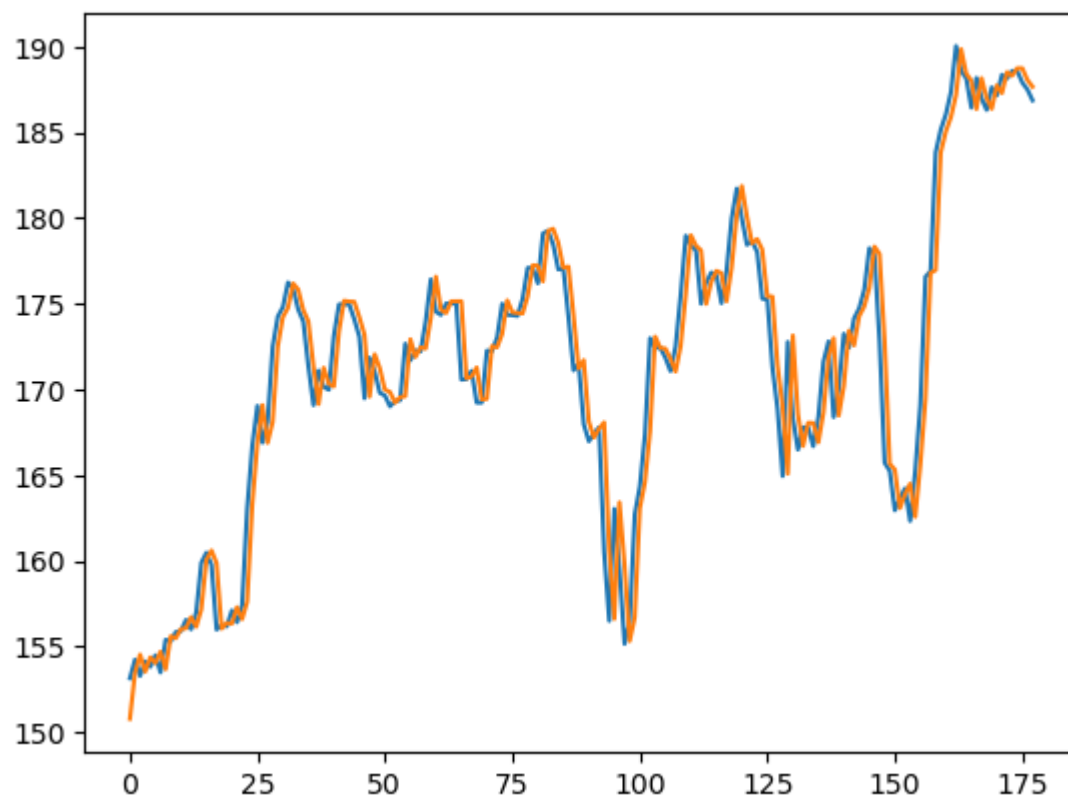

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```

```
1/1 [=====] - 0s 37ms/step  
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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_resaped = train_scaled[:, 0].reshape(len(train_scaled), 1, 1)
lstm_model.predict(train_resaped, 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)

    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

1/1 [=====] - 0s 35ms/step

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

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

1/1 [=====] - 0s 32ms/step

1/1 [=====] - 0s 35ms/step

1/1 [=====] - 0s 38ms/step

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

1/1 [=====] - 0s 35ms/step

1/1 [=====] - 0s 32ms/step

1/1 [=====] - 0s 38ms/step

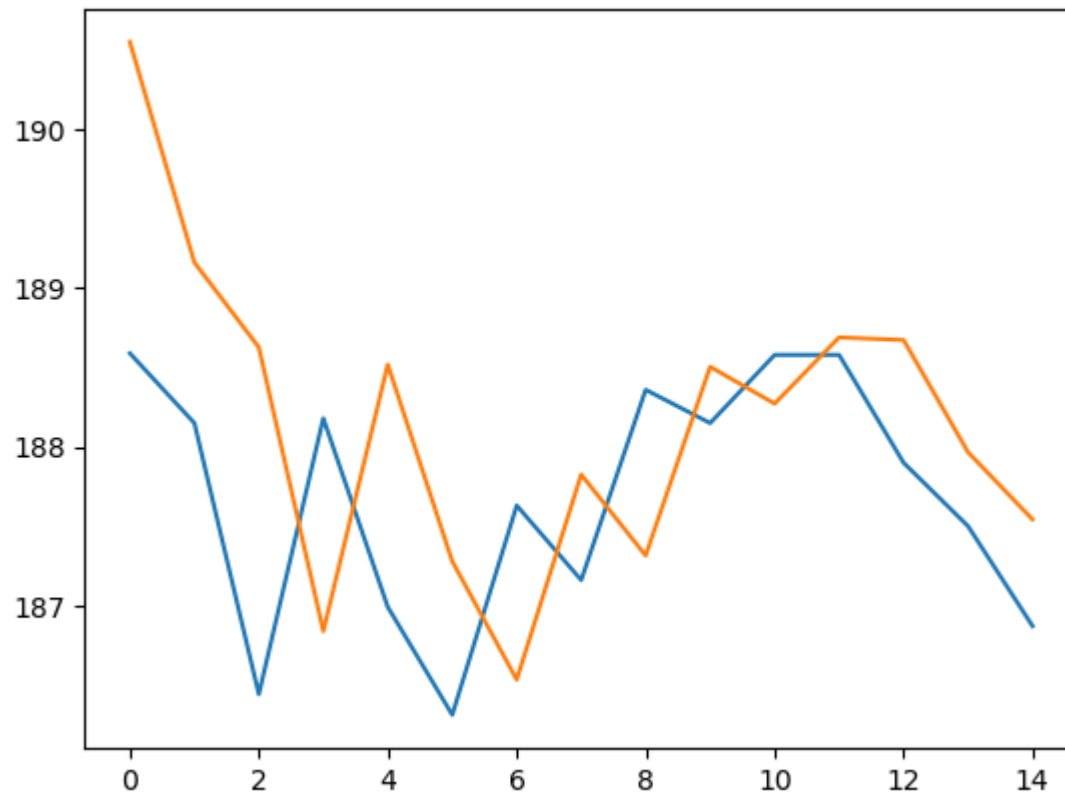
1/1 [=====] - 0s 31ms/step

1/1 [=====] - 0s 29ms/step

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

1/1 [=====] - 0s 33ms/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_resaped = train_scaled[:, 0].reshape(len(train_scaled), 1, 1)
lstm_model.predict(train_resaped, 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
1/1 [=====] - 0s 30ms/step
Month=1, Predicted=150.858546, Expected=153.140000
1/1 [=====] - 0s 31ms/step
Month=2, Predicted=153.036291, Expected=154.230000
1/1 [=====] - 0s 30ms/step
Month=3, Predicted=154.275633, Expected=153.280000
1/1 [=====] - 0s 35ms/step
Month=4, Predicted=153.547355, Expected=154.120000
1/1 [=====] - 0s 35ms/step
Month=5, Predicted=154.192395, Expected=153.810000
1/1 [=====] - 0s 37ms/step
Month=6, Predicted=154.008013, Expected=154.480000
1/1 [=====] - 0s 34ms/step
Month=7, Predicted=154.570775, Expected=153.480000
1/1 [=====] - 0s 32ms/step
Month=8, Predicted=153.752692, Expected=155.390000
1/1 [=====] - 0s 33ms/step
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
1/1 [=====] - 0s 45ms/step
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
1/1 [=====] - 0s 30ms/step
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
1/1 [=====] - 0s 37ms/step
Month=20, Predicted=156.384414, Expected=156.170000
1/1 [=====] - 0s 37ms/step
```

```
Month=21, Predicted=156.342808, Expected=157.100000
1/1 [=====] - 0s 32ms/step
Month=22, Predicted=157.162721, Expected=156.410000
1/1 [=====] - 0s 38ms/step
Month=23, Predicted=156.649385, Expected=157.410000
1/1 [=====] - 0s 38ms/step
Month=24, Predicted=157.465226, Expected=163.050000
1/1 [=====] - 0s 34ms/step
Month=25, Predicted=162.743349, Expected=166.720000
1/1 [=====] - 0s 34ms/step
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
1/1 [=====] - 0s 32ms/step
Month=29, Predicted=168.141868, Expected=172.500000
1/1 [=====] - 0s 33ms/step
Month=30, Predicted=172.257352, Expected=174.250000
1/1 [=====] - 0s 32ms/step
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
1/1 [=====] - 0s 41ms/step
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
1/1 [=====] - 0s 37ms/step
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
1/1 [=====] - 0s 30ms/step
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
1/1 [=====] - 0s 32ms/step
```

Month=43, Predicted=174.930076, Expected=174.960000
1/1 [=====] - 0s 32ms/step
Month=44, Predicted=175.124030, Expected=174.970000
1/1 [=====] - 0s 36ms/step
Month=45, Predicted=175.132932, Expected=174.090000
1/1 [=====] - 0s 42ms/step
Month=46, Predicted=174.349859, Expected=173.070000
1/1 [=====] - 0s 33ms/step
Month=47, Predicted=173.344823, Expected=169.480000
1/1 [=====] - 0s 39ms/step
Month=48, Predicted=169.994333, Expected=171.850000
1/1 [=====] - 0s 31ms/step
Month=49, Predicted=171.766633, Expected=171.050000
1/1 [=====] - 0s 32ms/step
Month=50, Predicted=171.301260, Expected=169.800000
1/1 [=====] - 0s 35ms/step
Month=51, Predicted=170.099136, Expected=169.640000
1/1 [=====] - 0s 34ms/step
Month=52, Predicted=169.821582, Expected=169.010000
1/1 [=====] - 0s 34ms/step
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
1/1 [=====] - 0s 32ms/step
Month=59, Predicted=172.389517, Expected=173.970000
1/1 [=====] - 0s 32ms/step
Month=60, Predicted=173.947117, Expected=176.420000
1/1 [=====] - 0s 39ms/step
Month=61, Predicted=176.329162, Expected=174.540000
1/1 [=====] - 0s 30ms/step
Month=62, Predicted=174.903528, Expected=174.350000
1/1 [=====] - 0s 33ms/step
Month=63, Predicted=174.534871, Expected=175.010000
1/1 [=====] - 0s 41ms/step
Month=64, Predicted=175.101860, Expected=175.010000
1/1 [=====] - 0s 36ms/step

```
Month=65, Predicted=175.174030, Expected=175.010000
1/1 [=====] - 0s 35ms/step
Month=66, Predicted=175.174030, Expected=170.570000
1/1 [=====] - 0s 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
1/1 [=====] - 0s 35ms/step
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
1/1 [=====] - 0s 29ms/step
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 [=====] - 0s 32ms/step
Month=81, Predicted=177.254030, Expected=176.190000
1/1 [=====] - 0s 31ms/step
Month=82, Predicted=176.452004, Expected=179.100000
1/1 [=====] - 0s 33ms/step
Month=83, Predicted=178.967885, Expected=179.260000
1/1 [=====] - 0s 30ms/step
Month=84, Predicted=179.406473, Expected=178.460000
1/1 [=====] - 0s 32ms/step
Month=85, Predicted=178.711260, Expected=177.000000
1/1 [=====] - 0s 31ms/step
Month=86, Predicted=177.320993, Expected=177.040000
1/1 [=====] - 0s 32ms/step
```

```
Month=87, Predicted=177.199640, Expected=174.220000
1/1 [=====] - 0s 31ms/step
Month=88, Predicted=174.671485, Expected=171.110000
1/1 [=====] - 0s 31ms/step
Month=89, Predicted=171.586215, Expected=171.510000
1/1 [=====] - 0s 32ms/step
Month=90, Predicted=171.630186, Expected=167.960000
1/1 [=====] - 0s 40ms/step
Month=91, Predicted=168.471295, Expected=166.970000
1/1 [=====] - 0s 36ms/step
Month=92, Predicted=167.241626, Expected=167.430000
1/1 [=====] - 0s 29ms/step
Month=93, Predicted=167.543631, Expected=167.780000
1/1 [=====] - 0s 33ms/step
Month=94, Predicted=167.905654, Expected=160.500000
1/1 [=====] - 0s 31ms/step
Month=95, Predicted=161.180099, Expected=156.490000
1/1 [=====] - 0s 39ms/step
Month=96, Predicted=157.034645, Expected=163.030000
1/1 [=====] - 0s 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
```

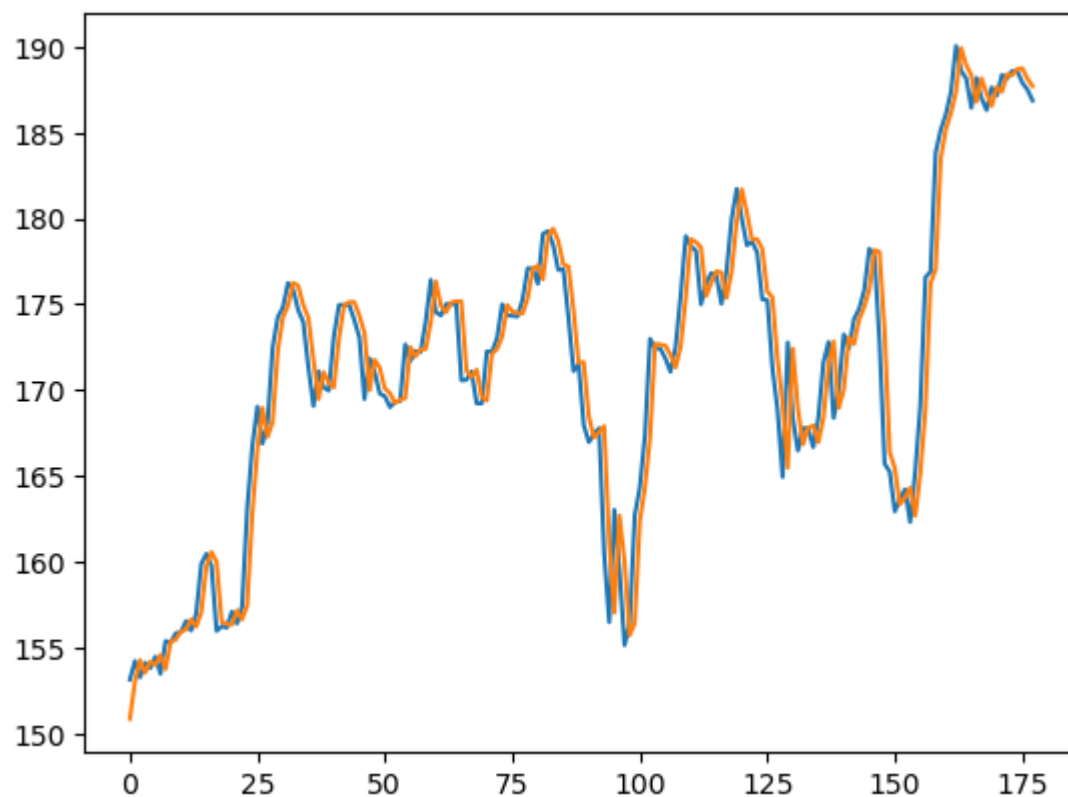
Month=109, Predicted=172.509891, Expected=175.500000
1/1 [=====] - 0s 40ms/step
Month=110, Predicted=175.360162, Expected=178.970000
1/1 [=====] - 0s 30ms/step
Month=111, Predicted=178.791846, Expected=178.390000
1/1 [=====] - 0s 34ms/step
Month=112, Predicted=178.617458, Expected=178.120000
1/1 [=====] - 0s 32ms/step
Month=113, Predicted=178.313635, Expected=175.000000
1/1 [=====] - 0s 37ms/step
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
1/1 [=====] - 0s 32ms/step
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
1/1 [=====] - 0s 36ms/step
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
1/1 [=====] - 0s 39ms/step
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
1/1 [=====] - 0s 30ms/step
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
1/1 [=====] - 0s 42ms/step

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
1/1 [=====] - 0s 38ms/step
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
1/1 [=====] - 0s 33ms/step
Month=162, Predicted=186.117015, Expected=187.360000
1/1 [=====] - 0s 32ms/step
Month=163, Predicted=187.382408, Expected=190.040000
1/1 [=====] - 0s 34ms/step
Month=164, Predicted=189.928157, Expected=188.590000
1/1 [=====] - 0s 36ms/step
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
1/1 [=====] - 0s 42ms/step
Month=173, Predicted=188.393978, Expected=188.150000
1/1 [=====] - 0s 32ms/step
Month=174, Predicted=188.337063, Expected=188.580000
1/1 [=====] - 0s 37ms/step


```
Month=175, Predicted=188.696908, Expected=188.580000  
1/1 [=====] - 0s 38ms/step  
Month=176, Predicted=188.744030, Expected=187.900000  
1/1 [=====] - 0s 33ms/step  
Month=177, Predicted=188.138303, Expected=187.500000  
1/1 [=====] - 0s 34ms/step  
Month=178, Predicted=187.707850, Expected=186.870000
```

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_resaped = train_scaled[:, 0].reshape(len(train_scaled), 1, 1)
lstm_model.predict(train_resaped, 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)

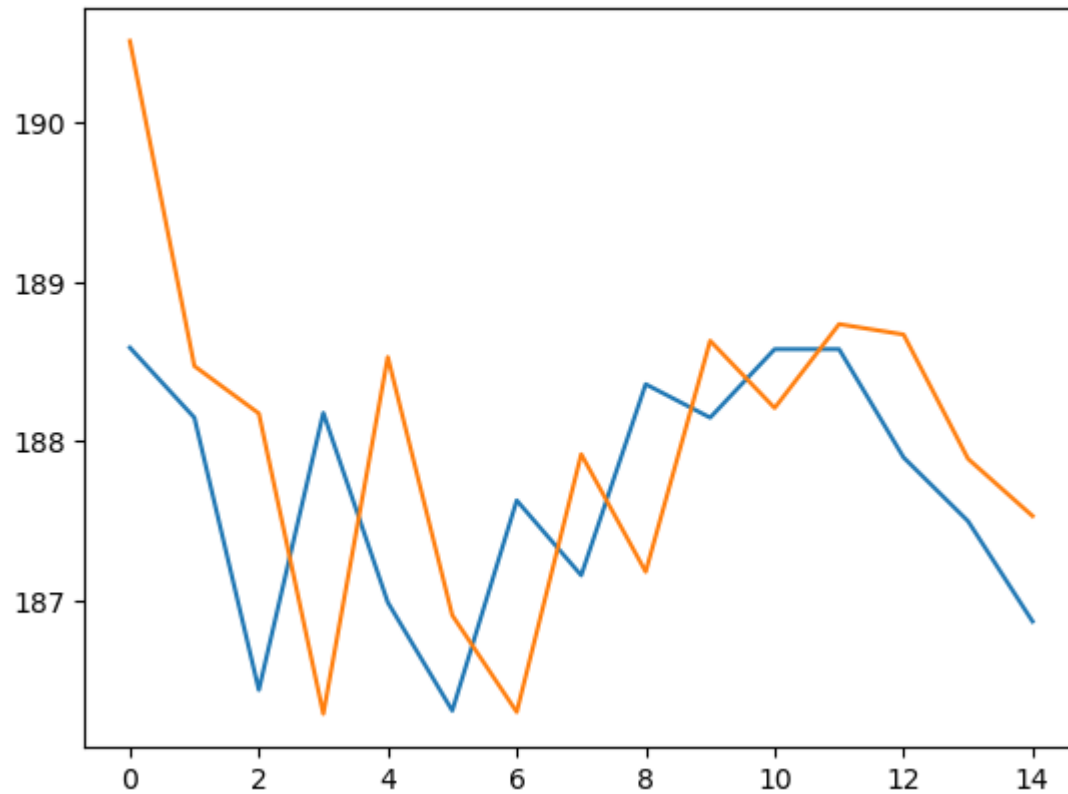
    yhat = inverse_the_difference(raw_values, yhat, len(test_scaled)-i+1)
    # store forecast
    predictions.append(yhat)
    expected = raw_values[len(train) + i + 1]
    print('Month=%d, Predicted=%f, Expected=%f' % (i+1, yhat, expected))

##print("X and y data : ", X , " y = ", y )
#print("yhat = ", yhat)
# report performance
rmse = sqrt(mean_squared_error(raw_values[-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
1/1 [=====] - 0s 30ms/step
Month=2, Predicted=188.473870, Expected=188.150000
1/1 [=====] - 0s 32ms/step
Month=3, Predicted=188.176493, Expected=186.440000
1/1 [=====] - 0s 39ms/step
Month=4, Predicted=186.289961, Expected=188.180000
1/1 [=====] - 0s 37ms/step
Month=5, Predicted=188.530675, Expected=186.990000
1/1 [=====] - 0s 33ms/step
Month=6, Predicted=186.909095, Expected=186.310000
1/1 [=====] - 0s 35ms/step
Month=7, Predicted=186.301352, Expected=187.630000
1/1 [=====] - 0s 30ms/step
Month=8, Predicted=187.920263, Expected=187.160000
1/1 [=====] - 0s 32ms/step
Month=9, Predicted=187.182069, Expected=188.360000
1/1 [=====] - 0s 32ms/step
Month=10, Predicted=188.632629, Expected=188.150000
1/1 [=====] - 0s 34ms/step
Month=11, Predicted=188.210663, Expected=188.580000
1/1 [=====] - 0s 36ms/step
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
1/1 [=====] - 0s 29ms/step
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_resaped = train_scaled[:, 0].reshape(len(train_scaled), 1, 1)
cnn_model.predict(train_resaped, 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, 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('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
1/1 [=====] - 0s 33ms/step
Month=1, Predicted=150.999398, Expected=153.140000
1/1 [=====] - 0s 30ms/step
Month=2, Predicted=152.803142, Expected=154.230000
1/1 [=====] - 0s 31ms/step
Month=3, Predicted=154.193240, Expected=153.280000
1/1 [=====] - 0s 32ms/step
Month=4, Predicted=153.651373, Expected=154.120000
1/1 [=====] - 0s 31ms/step
Month=5, Predicted=154.133256, Expected=153.810000
1/1 [=====] - 0s 33ms/step
Month=6, Predicted=154.053331, Expected=154.480000
1/1 [=====] - 0s 33ms/step
Month=7, Predicted=154.527267, Expected=153.480000
1/1 [=====] - 0s 33ms/step
Month=8, Predicted=153.861376, Expected=155.390000
1/1 [=====] - 0s 30ms/step
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
1/1 [=====] - 0s 33ms/step
Month=15, Predicted=156.973246, Expected=159.880000
1/1 [=====] - 0s 30ms/step
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
1/1 [=====] - 0s 32ms/step
Month=19, Predicted=156.917557, Expected=156.250000
1/1 [=====] - 0s 31ms/step
Month=20, Predicted=156.377293, Expected=156.170000
1/1 [=====] - 0s 32ms/step
```

Month=21, Predicted=156.367316, Expected=157.100000
1/1 [=====] - 0s 35ms/step
Month=22, Predicted=157.095250, Expected=156.410000
1/1 [=====] - 0s 33ms/step
Month=23, Predicted=156.729356, Expected=157.410000
1/1 [=====] - 0s 40ms/step
Month=24, Predicted=157.391245, Expected=163.050000
1/1 [=====] - 0s 33ms/step
Month=25, Predicted=162.102943, Expected=166.720000
1/1 [=====] - 0s 34ms/step
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
1/1 [=====] - 0s 35ms/step
Month=29, Predicted=168.047231, Expected=172.500000
1/1 [=====] - 0s 35ms/step
Month=30, Predicted=171.803025, Expected=174.250000
1/1 [=====] - 0s 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
1/1 [=====] - 0s 38ms/step
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
1/1 [=====] - 0s 32ms/step
Month=38, Predicted=169.713458, Expected=171.100000
1/1 [=====] - 0s 34ms/step
Month=39, Predicted=170.877179, Expected=170.150000
1/1 [=====] - 0s 37ms/step
Month=40, Predicted=170.521373, Expected=169.980000
1/1 [=====] - 0s 33ms/step
Month=41, Predicted=170.195322, Expected=173.140000
1/1 [=====] - 0s 32ms/step
Month=42, Predicted=172.689105, Expected=174.960000
1/1 [=====] - 0s 33ms/step

```
Month=43, Predicted=174.777192, Expected=174.960000
1/1 [=====] - 0s 32ms/step
Month=44, Predicted=175.141311, Expected=174.970000
1/1 [=====] - 0s 33ms/step
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
1/1 [=====] - 0s 41ms/step
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 [=====] - 0s 39ms/step
Month=51, Predicted=170.231392, Expected=169.640000
1/1 [=====] - 0s 32ms/step
Month=52, Predicted=169.853321, Expected=169.010000
1/1 [=====] - 0s 30ms/step
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
1/1 [=====] - 0s 30ms/step
Month=56, Predicted=172.191096, Expected=171.700000
1/1 [=====] - 0s 31ms/step
Month=57, Predicted=172.075374, Expected=172.270000
1/1 [=====] - 0s 34ms/step
Month=58, Predicted=172.337274, Expected=172.220000
1/1 [=====] - 0s 33ms/step
Month=59, Predicted=172.411314, Expected=173.970000
1/1 [=====] - 0s 29ms/step
Month=60, Predicted=173.801197, Expected=176.420000
1/1 [=====] - 0s 29ms/step
Month=61, Predicted=176.111151, Expected=174.540000
1/1 [=====] - 0s 30ms/step
Month=62, Predicted=175.097433, Expected=174.350000
1/1 [=====] - 0s 32ms/step
Month=63, Predicted=174.569323, Expected=175.010000
1/1 [=====] - 0s 33ms/step
Month=64, Predicted=175.059268, Expected=175.010000
1/1 [=====] - 0s 29ms/step
```



```
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
1/1 [=====] - 0s 30ms/step
Month=69, Predicted=171.165279, Expected=169.230000
1/1 [=====] - 0s 32ms/step
Month=70, Predicted=169.781431, Expected=169.230000
1/1 [=====] - 0s 33ms/step
Month=71, Predicted=169.411311, Expected=172.260000
1/1 [=====] - 0s 32ms/step
Month=72, Predicted=171.835113, Expected=172.230000
1/1 [=====] - 0s 33ms/step
Month=73, Predicted=172.417313, Expected=173.030000
1/1 [=====] - 0s 33ms/step
Month=74, Predicted=173.051259, Expected=175.000000
1/1 [=====] - 0s 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
1/1 [=====] - 0s 33ms/step
Month=78, Predicted=174.479313, Expected=175.280000
1/1 [=====] - 0s 31ms/step
Month=79, Predicted=175.263246, Expected=177.090000
1/1 [=====] - 0s 32ms/step
Month=80, Predicted=176.909193, Expected=177.090000
1/1 [=====] - 0s 30ms/step
Month=81, Predicted=177.271311, Expected=176.190000
1/1 [=====] - 0s 31ms/step
Month=82, Predicted=176.551369, Expected=179.100000
1/1 [=====] - 0s 33ms/step
Month=83, Predicted=178.699121, Expected=179.260000
1/1 [=====] - 0s 30ms/step
Month=84, Predicted=179.409300, Expected=178.460000
1/1 [=====] - 0s 29ms/step
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
```

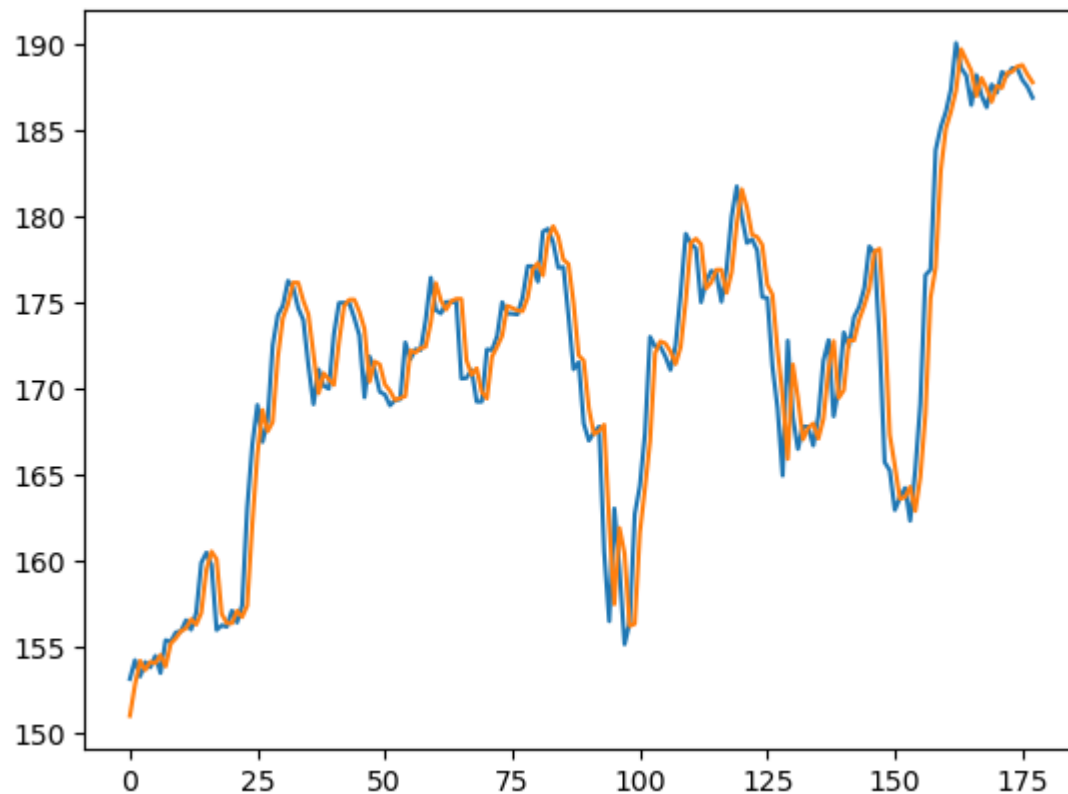
Month=87, Predicted=177.213308, Expected=174.220000
1/1 [=====] - 0s 32ms/step
Month=88, Predicted=174.965494, Expected=171.110000
1/1 [=====] - 0s 30ms/step
Month=89, Predicted=171.913513, Expected=171.510000
1/1 [=====] - 0s 33ms/step
Month=90, Predicted=171.611285, Expected=167.960000
1/1 [=====] - 0s 30ms/step
Month=91, Predicted=168.851542, Expected=166.970000
1/1 [=====] - 0s 31ms/step
Month=92, Predicted=167.349375, Expected=167.430000
1/1 [=====] - 0s 31ms/step
Month=93, Predicted=167.519281, Expected=167.780000
1/1 [=====] - 0s 32ms/step
Month=94, Predicted=167.891288, Expected=160.500000
1/1 [=====] - 0s 33ms/step
Month=95, Predicted=162.137785, Expected=156.490000
1/1 [=====] - 0s 30ms/step
Month=96, Predicted=157.473572, Expected=163.030000
1/1 [=====] - 0s 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
1/1 [=====] - 0s 33ms/step
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
1/1 [=====] - 0s 36ms/step
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
1/1 [=====] - 0s 29ms/step
Month=117, Predicted=176.881320, Expected=175.030000
1/1 [=====] - 0s 32ms/step
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
1/1 [=====] - 0s 39ms/step
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
1/1 [=====] - 0s 29ms/step
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
1/1 [=====] - 0s 33ms/step
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
1/1 [=====] - 0s 30ms/step
Month=151, Predicted=165.517342, Expected=162.940000
1/1 [=====] - 0s 29ms/step
Month=152, Predicted=163.581461, Expected=163.650000
1/1 [=====] - 0s 28ms/step

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
1/1 [=====] - 0s 31ms/step
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
1/1 [=====] - 0s 31ms/step
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
1/1 [=====] - 0s 36ms/step
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
1/1 [=====] - 0s 37ms/step
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

```
Month=175, Predicted=188.675283, Expected=188.580000  
1/1 [=====] - 0s 35ms/step  
Month=176, Predicted=188.761311, Expected=187.900000  
1/1 [=====] - 0s 36ms/step  
Month=177, Predicted=188.217355, Expected=187.500000  
1/1 [=====] - 0s 32ms/step  
Month=178, Predicted=187.761337, Expected=186.870000  
Test RMSE: 2.478
```



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_resaped = train_scaled[:, 0].reshape(len(train_scaled), 1, 1)
cnn_model.predict(train_resaped, batch_size=1)

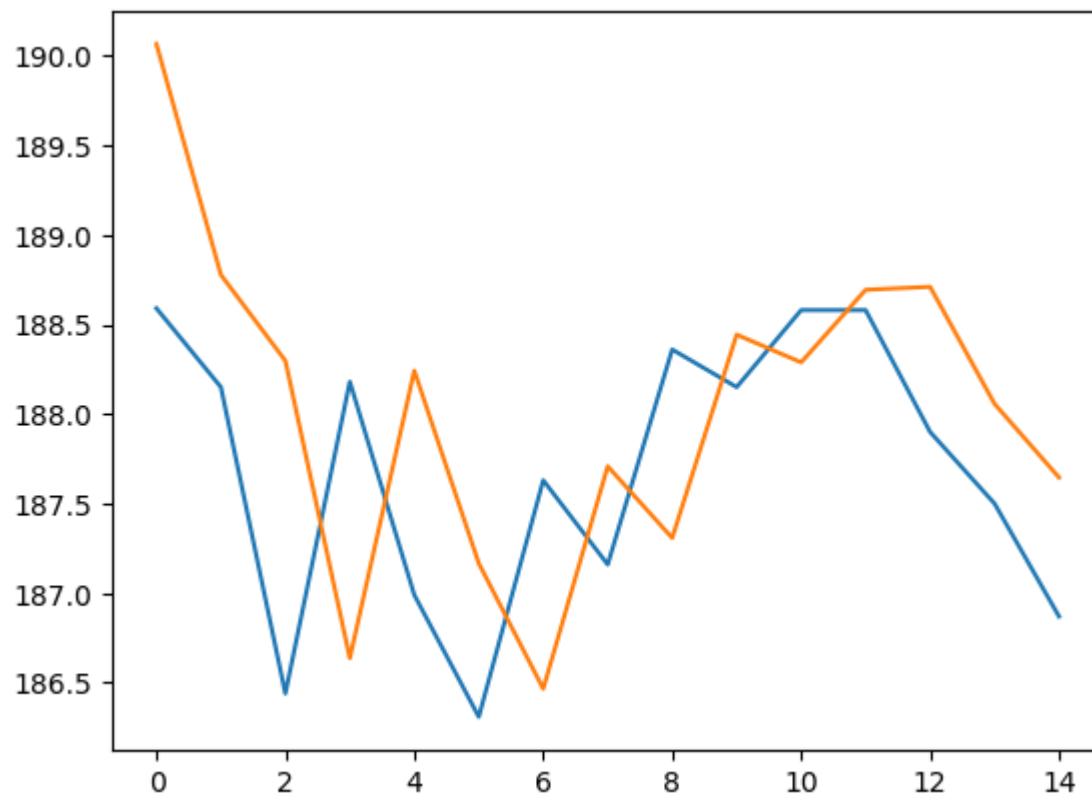
# walk-forward validation on the test data
predictions = list()
for i in range(len(test_scaled)):
    # make one-step forecast
    X, y = test_scaled[i, 0:-1], test_scaled[i, -1]
    yhat = forecast_cnn(cnn_model, 1, X)
    # invert scaling
    yhat = invert_scale(scaler, X, yhat)

    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, 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]), 1
X.shape[2]) 1
875/875 [=====] - 1s 2ms/step
1/1 [=====] - 0s 37ms/step
Month=1, Predicted=190.064803, Expected=188.590000
1/1 [=====] - 0s 32ms/step
Month=2, Predicted=188.776842, Expected=188.150000
1/1 [=====] - 0s 30ms/step
Month=3, Predicted=188.297215, Expected=186.440000
1/1 [=====] - 0s 27ms/step
Month=4, Predicted=186.637043, Expected=188.180000
1/1 [=====] - 0s 29ms/step
Month=5, Predicted=188.241683, Expected=186.990000
1/1 [=====] - 0s 32ms/step
Month=6, Predicted=187.166641, Expected=186.310000
1/1 [=====] - 0s 32ms/step
Month=7, Predicted=186.466631, Expected=187.630000
1/1 [=====] - 0s 33ms/step
Month=8, Predicted=187.708162, Expected=187.160000
1/1 [=====] - 0s 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 [=====] - 0s 30ms/step
Month=12, Predicted=188.693081, Expected=188.580000
1/1 [=====] - 0s 31ms/step
Month=13, Predicted=188.709952, Expected=187.900000
1/1 [=====] - 0s 32ms/step
Month=14, Predicted=188.056631, Expected=187.500000
1/1 [=====] - 0s 32ms/step
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_resaped = train_scaled[:, 0].reshape(len(train_scaled), 1, 1)
bilstm_model.predict(train_resaped, 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)

    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 [=====] - 2s 2ms/step
1/1 [=====] - 0s 27ms/step
Month=1, Predicted=150.857409, Expected=153.140000
1/1 [=====] - 0s 32ms/step
Month=2, Predicted=153.294014, Expected=154.230000
1/1 [=====] - 0s 36ms/step
Month=3, Predicted=154.347763, Expected=153.280000
1/1 [=====] - 0s 30ms/step
Month=4, Predicted=153.464256, Expected=154.120000
1/1 [=====] - 0s 34ms/step
Month=5, Predicted=154.264055, Expected=153.810000
1/1 [=====] - 0s 33ms/step
Month=6, Predicted=153.980908, Expected=154.480000
1/1 [=====] - 0s 31ms/step
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
1/1 [=====] - 0s 28ms/step
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
1/1 [=====] - 0s 37ms/step
Month=15, Predicted=157.120026, Expected=159.880000
1/1 [=====] - 0s 32ms/step
Month=16, Predicted=159.888880, Expected=160.470000
1/1 [=====] - 0s 33ms/step
Month=17, Predicted=160.543346, Expected=159.760000
1/1 [=====] - 0s 33ms/step
Month=18, Predicted=159.910294, Expected=155.980000
1/1 [=====] - 0s 29ms/step
Month=19, Predicted=156.259854, Expected=156.250000
1/1 [=====] - 0s 32ms/step
Month=20, Predicted=156.498853, Expected=156.170000
1/1 [=====] - 0s 32ms/step
```

Month=21, Predicted=156.386530, Expected=157.100000
1/1 [=====] - 0s 37ms/step
Month=22, Predicted=157.258985, Expected=156.410000
1/1 [=====] - 0s 29ms/step
Month=23, Predicted=156.603077, Expected=157.410000
1/1 [=====] - 0s 34ms/step
Month=24, Predicted=157.552376, Expected=163.050000
1/1 [=====] - 0s 32ms/step
Month=25, Predicted=162.902787, Expected=166.720000
1/1 [=====] - 0s 32ms/step
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
1/1 [=====] - 0s 31ms/step
Month=29, Predicted=168.208416, Expected=172.500000
1/1 [=====] - 0s 30ms/step
Month=30, Predicted=172.400253, Expected=174.250000
1/1 [=====] - 0s 28ms/step
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
1/1 [=====] - 0s 33ms/step
Month=34, Predicted=175.998398, Expected=174.670000
1/1 [=====] - 0s 31ms/step
Month=35, Predicted=174.857930, Expected=173.970000
1/1 [=====] - 0s 32ms/step
Month=36, Predicted=174.177477, Expected=171.340000
1/1 [=====] - 0s 30ms/step
Month=37, Predicted=171.617155, Expected=169.080000
1/1 [=====] - 0s 32ms/step
Month=38, Predicted=169.392377, Expected=171.100000
1/1 [=====] - 0s 30ms/step
Month=39, Predicted=171.292491, Expected=170.150000
1/1 [=====] - 0s 30ms/step
Month=40, Predicted=170.367778, Expected=169.980000
1/1 [=====] - 0s 30ms/step
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 [=====] - 0s 30ms/step
Month=44, Predicted=175.064707, Expected=174.970000
1/1 [=====] - 0s 32ms/step
Month=45, Predicted=175.104008, Expected=174.090000
1/1 [=====] - 0s 30ms/step
Month=46, Predicted=174.275814, Expected=173.070000
1/1 [=====] - 0s 33ms/step
Month=47, Predicted=173.288043, Expected=169.480000
1/1 [=====] - 0s 29ms/step
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 [=====] - 0s 31ms/step
Month=51, Predicted=170.039409, Expected=169.640000
1/1 [=====] - 0s 33ms/step
Month=52, Predicted=169.859869, Expected=169.010000
1/1 [=====] - 0s 32ms/step
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 [=====] - 0s 31ms/step
Month=58, Predicted=172.404471, Expected=172.220000
1/1 [=====] - 0s 28ms/step
Month=59, Predicted=172.374318, Expected=173.970000
1/1 [=====] - 0s 37ms/step
Month=60, Predicted=174.052254, Expected=176.420000
1/1 [=====] - 0s 31ms/step
Month=61, Predicted=176.427225, Expected=174.540000
1/1 [=====] - 0s 30ms/step
Month=62, Predicted=174.716400, Expected=174.350000
1/1 [=====] - 0s 30ms/step
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 [=====] - 0s 30ms/step
Month=66, Predicted=175.175282, Expected=170.570000
1/1 [=====] - 0s 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
1/1 [=====] - 0s 30ms/step
Month=70, Predicted=169.488699, Expected=169.230000
1/1 [=====] - 0s 33ms/step
Month=71, Predicted=169.459085, Expected=172.260000
1/1 [=====] - 0s 30ms/step
Month=72, Predicted=172.327214, Expected=172.230000
1/1 [=====] - 0s 32ms/step
Month=73, Predicted=172.359743, Expected=173.030000
1/1 [=====] - 0s 32ms/step
Month=74, Predicted=173.143125, Expected=175.000000
1/1 [=====] - 0s 32ms/step
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
1/1 [=====] - 0s 30ms/step
Month=78, Predicted=174.454049, Expected=175.280000
1/1 [=====] - 0s 33ms/step
Month=79, Predicted=175.404470, Expected=177.090000
1/1 [=====] - 0s 30ms/step
Month=80, Predicted=177.152998, Expected=177.090000
1/1 [=====] - 0s 29ms/step
Month=81, Predicted=177.210481, Expected=176.190000
1/1 [=====] - 0s 29ms/step
Month=82, Predicted=176.369682, Expected=179.100000
1/1 [=====] - 0s 29ms/step
Month=83, Predicted=179.139579, Expected=179.260000
1/1 [=====] - 0s 29ms/step
Month=84, Predicted=179.367320, Expected=178.460000
1/1 [=====] - 0s 28ms/step
Month=85, Predicted=178.629350, Expected=177.000000
1/1 [=====] - 0s 30ms/step
Month=86, Predicted=177.223998, Expected=177.040000
1/1 [=====] - 0s 30ms/step
```

```
Month=87, Predicted=177.243153, Expected=174.220000
1/1 [=====] - 0s 30ms/step
Month=88, Predicted=174.500069, Expected=171.110000
1/1 [=====] - 0s 30ms/step
Month=89, Predicted=171.443784, Expected=171.510000
1/1 [=====] - 0s 32ms/step
Month=90, Predicted=171.790146, Expected=167.960000
1/1 [=====] - 0s 30ms/step
Month=91, Predicted=168.287831, Expected=166.970000
1/1 [=====] - 0s 35ms/step
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
1/1 [=====] - 0s 30ms/step
Month=95, Predicted=160.849476, Expected=156.490000
1/1 [=====] - 0s 33ms/step
Month=96, Predicted=156.928884, Expected=163.030000
1/1 [=====] - 0s 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
1/1 [=====] - 0s 33ms/step
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
1/1 [=====] - 0s 32ms/step
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
```

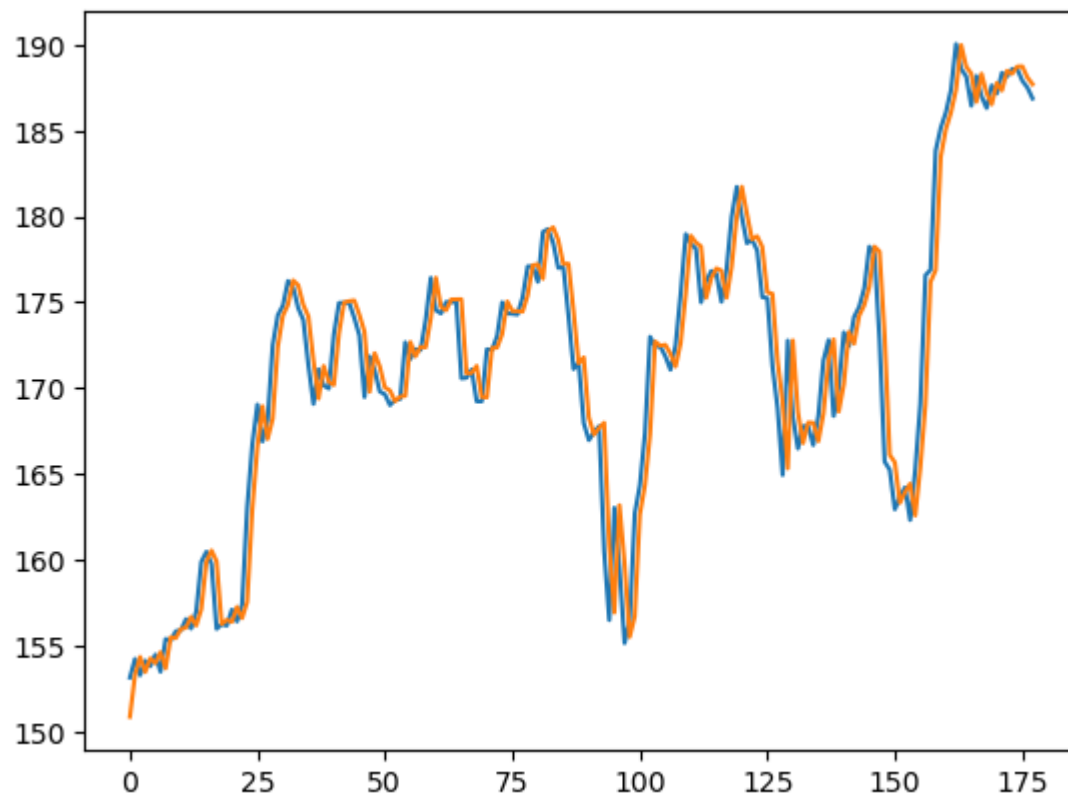
Month=109, Predicted=172.619448, Expected=175.500000
1/1 [=====] - 0s 30ms/step
Month=110, Predicted=175.496652, Expected=178.970000
1/1 [=====] - 0s 32ms/step
Month=111, Predicted=178.875880, Expected=178.390000
1/1 [=====] - 0s 30ms/step
Month=112, Predicted=178.477982, Expected=178.120000
1/1 [=====] - 0s 32ms/step
Month=113, Predicted=178.253578, Expected=175.000000
1/1 [=====] - 0s 30ms/step
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
1/1 [=====] - 0s 30ms/step
Month=117, Predicted=176.838589, Expected=175.030000
1/1 [=====] - 0s 30ms/step
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
1/1 [=====] - 0s 29ms/step
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
1/1 [=====] - 0s 39ms/step
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
1/1 [=====] - 0s 32ms/step
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
1/1 [=====] - 0s 30ms/step
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
1/1 [=====] - 0s 31ms/step
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
1/1 [=====] - 0s 30ms/step
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
1/1 [=====] - 0s 30ms/step
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
1/1 [=====] - 0s 29ms/step
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

```
Month=175, Predicted=188.724659, Expected=188.580000  
1/1 [=====] - 0s 33ms/step  
Month=176, Predicted=188.737415, Expected=187.900000  
1/1 [=====] - 0s 30ms/step  
Month=177, Predicted=188.090766, Expected=187.500000  
1/1 [=====] - 0s 32ms/step  
Month=178, Predicted=187.698435, Expected=186.870000
```

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_resaped = train_scaled[:, 0].reshape(len(train_scaled), 1, 1)
bilstm_model.predict(train_resaped, 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)

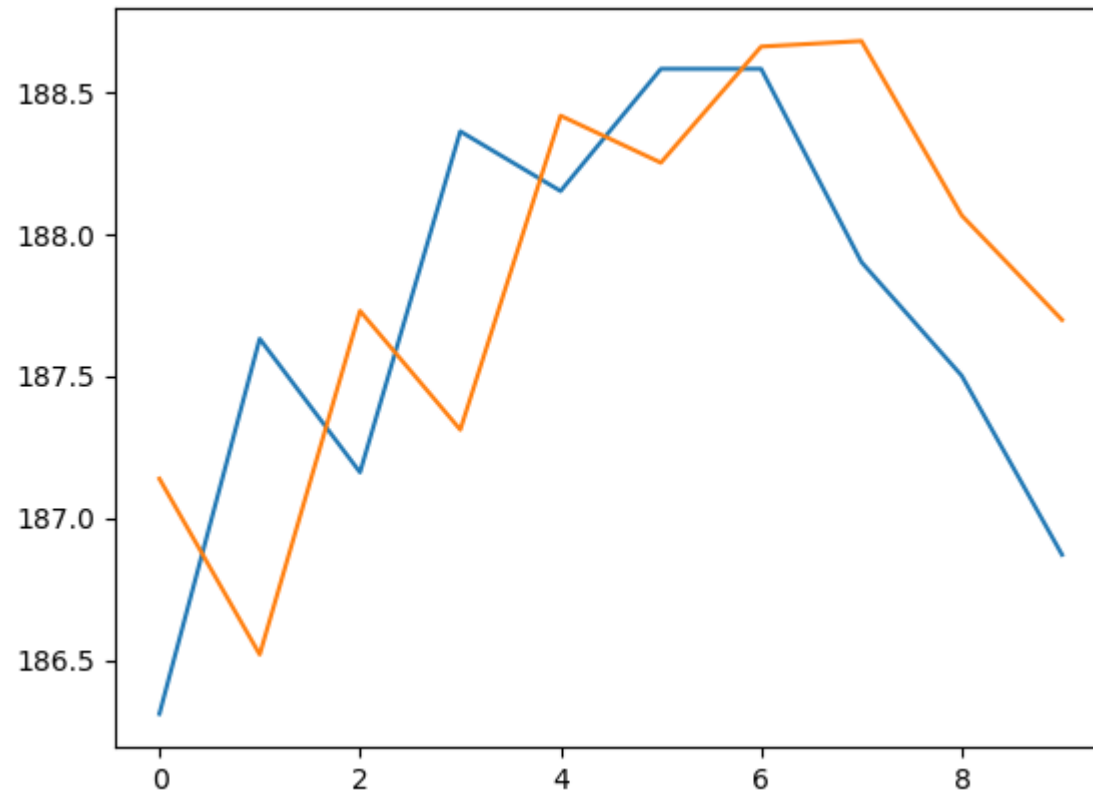
    yhat = inverse_the_difference(raw_values, yhat, len(test_scaled)-i+1)
    # store forecast
    predictions.append(yhat)
    expected = raw_values[len(train) + i + 1]
    print('Month=%d, Predicted=%f, Expected=%f' % (i+1, yhat, expected))

##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 [=====] - 0s 29ms/step
Month=1, Predicted=187.137314, Expected=186.310000
1/1 [=====] - 0s 28ms/step
Month=2, Predicted=186.518677, Expected=187.630000
1/1 [=====] - 0s 27ms/step
Month=3, Predicted=187.728263, Expected=187.160000
1/1 [=====] - 0s 31ms/step
Month=4, Predicted=187.309943, Expected=188.360000
1/1 [=====] - 0s 30ms/step
Month=5, Predicted=188.415160, Expected=188.150000
1/1 [=====] - 0s 28ms/step
Month=6, Predicted=188.249773, Expected=188.580000
1/1 [=====] - 0s 31ms/step
Month=7, Predicted=188.658451, Expected=188.580000
1/1 [=====] - 0s 31ms/step
Month=8, Predicted=188.678007, Expected=187.900000
1/1 [=====] - 0s 30ms/step
Month=9, Predicted=188.064169, Expected=187.500000
1/1 [=====] - 0s 27ms/step
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->statsmodels) (3.0.9)
 Requirement already satisfied: pytz>=2020.1 in c:\users\jaypa\anaconda3\lib\site-packages (from pandas>=0.25->statsmodels) (2022.1)
 Requirement already satisfied: python-dateutil>=2.8.1 in c:\users\jaypa\anaconda3\lib\site-packages (from pandas>=0.25->statsmodels) (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 failed to converge. Check mle_retvals

warnings.warn("Maximum Likelihood optimization failed to "

SARIMAX Results

```
=====
Dep. Variable:          y      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
```

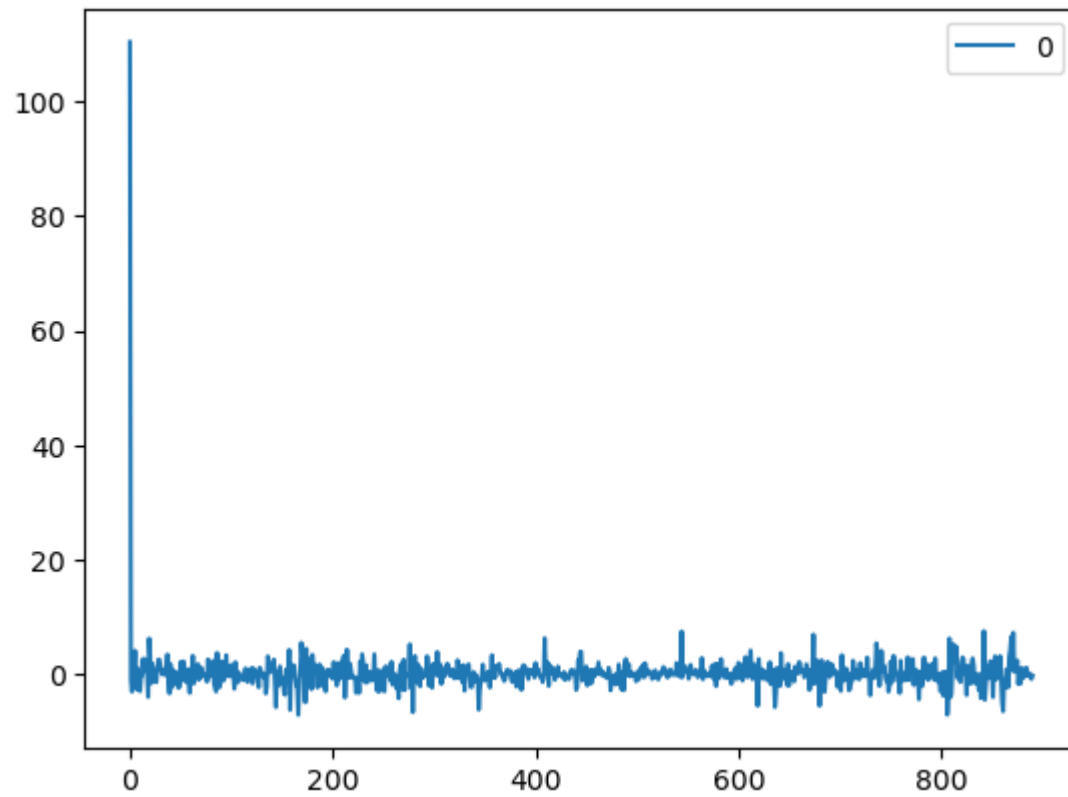
Covariance Type: opg

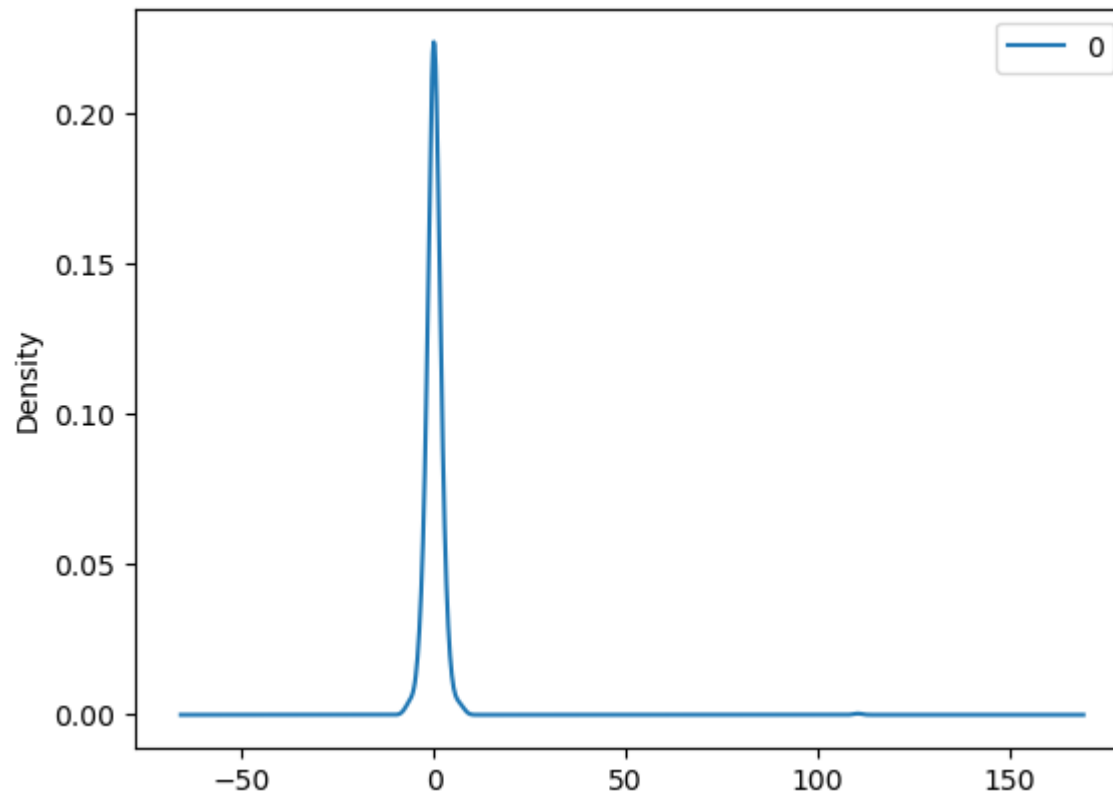
```
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
ar.L1         -1.3001        0.683      -1.903      0.057      -2.639      0.039
ar.L2         -0.8280        1.516      -0.546      0.585      -3.800      2.144
ar.L3          0.5055        1.932       0.262      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
=====
```

```
=====
Ljung-Box (L1) (Q):          0.46  Jarque-Bera (JB):          236.46
Prob(Q):                  0.50  Prob(JB):              0.00
Heteroskedasticity (H):      1.18  Skew:                  0.03
Prob(H) (two-sided):        0.15  Kurtosis:              5.52
=====
```

Warnings:

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





```
0
count  891.000000
mean    0.205665
std     4.121053
min    -7.087373
25%    -0.734104
50%     0.052547
75%     0.965916
max    110.380000
```

```
In [34]: from math import sqrt
from sklearn.metrics import mean_squared_error
X = data
size = int(len(X) * 0.66)
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=(5,1,0))
    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

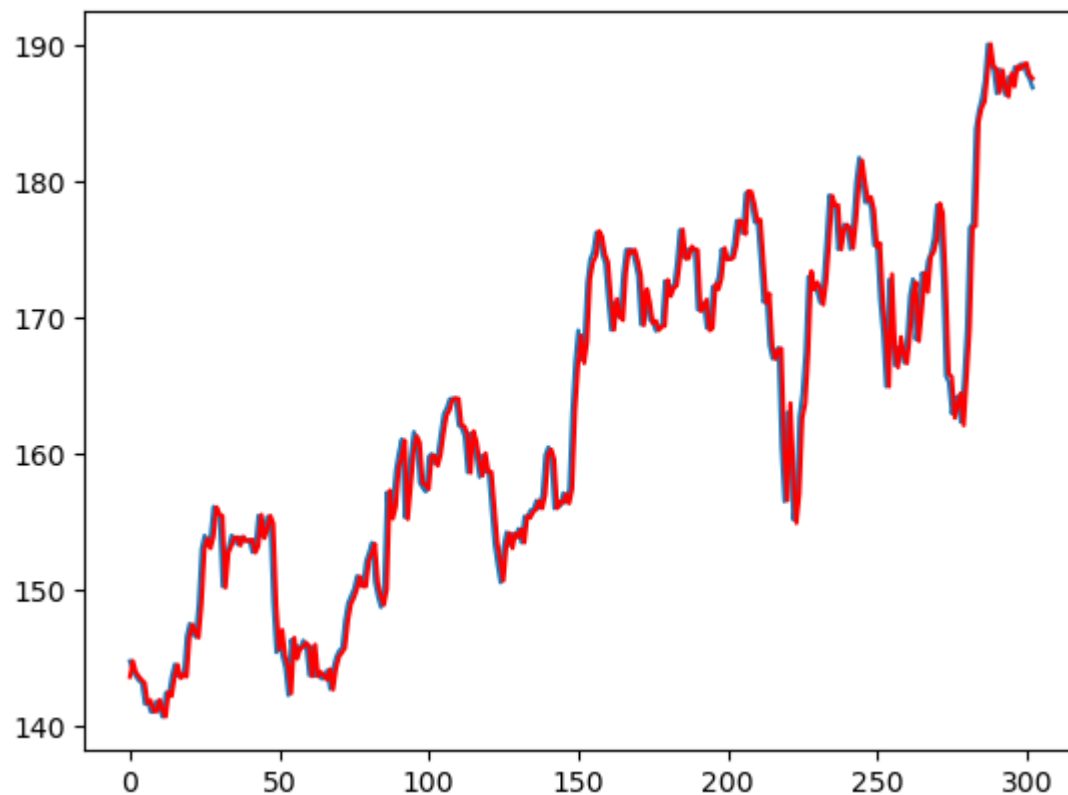
predicted=155.223972, expected=156.390000
predicted=156.113198, expected=158.810000
predicted=158.964885, expected=160.080000
predicted=159.844606, expected=161.060000
predicted=160.962914, expected=155.320000
predicted=155.190061, expected=157.480000
predicted=157.657067, expected=159.850000
predicted=160.060587, 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
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predicted=175.942899, expected=174.670000
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predicted=171.356851, expected=169.080000
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predicted=170.083702, expected=169.980000
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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
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predicted=172.327775, expected=173.970000
predicted=173.994698, expected=176.420000
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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
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predicted=172.073558, expected=173.030000
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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
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predicted=175.522977, expected=178.970000
predicted=178.929378, expected=178.390000
predicted=178.231151, expected=178.120000
predicted=178.247289, expected=175.000000
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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
```

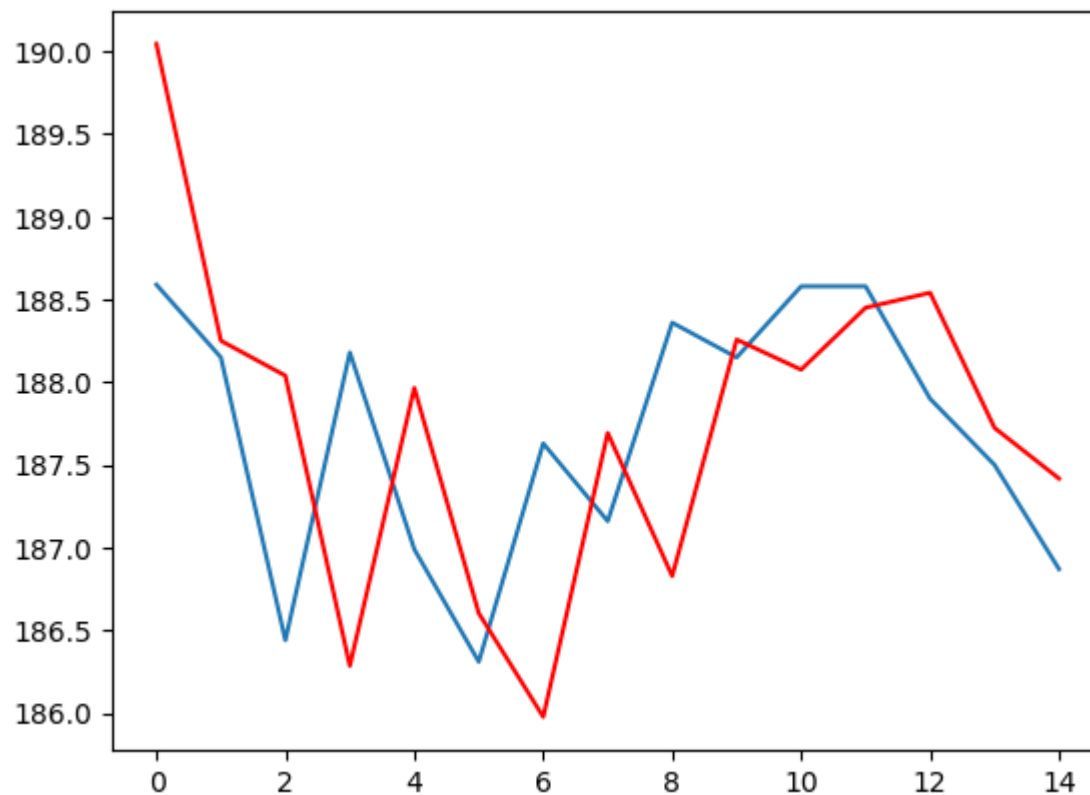


```
In [35]: from math import sqrt
from sklearn.metrics import mean_squared_error
X = data
size = 876
train, test = X[0:size], X[size:len(X)]
history = [x for x in train]
predictions = list()
# walk-forward validation
for t in range(len(test)):
    model = ARIMA(history, order=(5,1,1))
    model_fit = 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

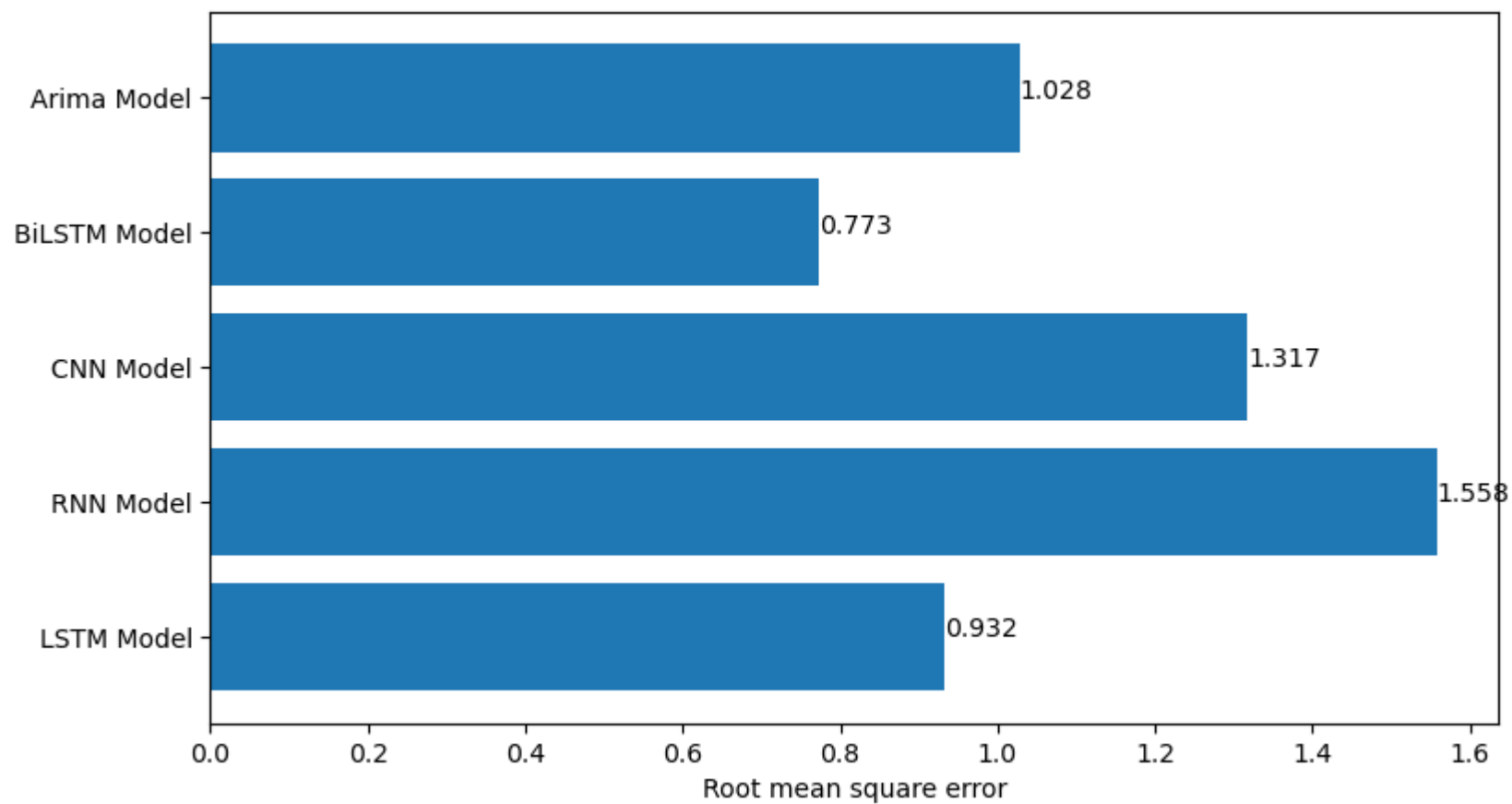
```
In [36]: plt.figure(figsize=(9, 5))

# models
Models_used = ["LSTM Model", "RNN Model", "CNN Model", "BiLSTM Model", "Arima Model"]

# metrics of the model in list format
rmse_of_models = [0.932, 1.558, 1.317, 0.773, 1.028]

plt.barh(Models_used, rmse_of_models)
plt.xlabel("Root mean square error")
for index, value in enumerate(rmse_of_models):
    plt.text(value, index,
             str(value))
```

```
plt.show()
```



Further Implementation

Gated Recurrent Unit (GRU) Neural Network

- In addition to the models discussed in the original research paper, we implemented the Gated Recurrent Unit (GRU) model as part of this project.

- **The GRU model is known for its efficiency and accuracy in handling sequential data, making it a suitable candidate for time series forecasting.**

```
In [37]: from tensorflow.keras.layers import GRU
```

```
In [38]: def fit_gru(train, batchSize, epoch):
    X, y = train[:, 0:-1], train[:, -1]
    X = X.reshape(X.shape[0], 1, X.shape[1])
    model = Sequential()
    model.add(GRU(units=64, activation='tanh', batch_input_shape=(batchSize, X.shape[1], X.shape[2])))
    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
```

```
In [39]: def forecast_gru(model, batch_size, X):
    X = X.reshape(1, 1, len(X))
    yhat = model.predict(X, batch_size=batch_size)
    return yhat[0,0]
```

```
In [40]: 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
gru_model = fit_gru(train_scaled, 1, 1)

# forecast
train_resaped = train_scaled[:, 0].reshape(len(train_scaled), 1, 1)
gru_model.predict(train_resaped, 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_gru(gru_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()
```



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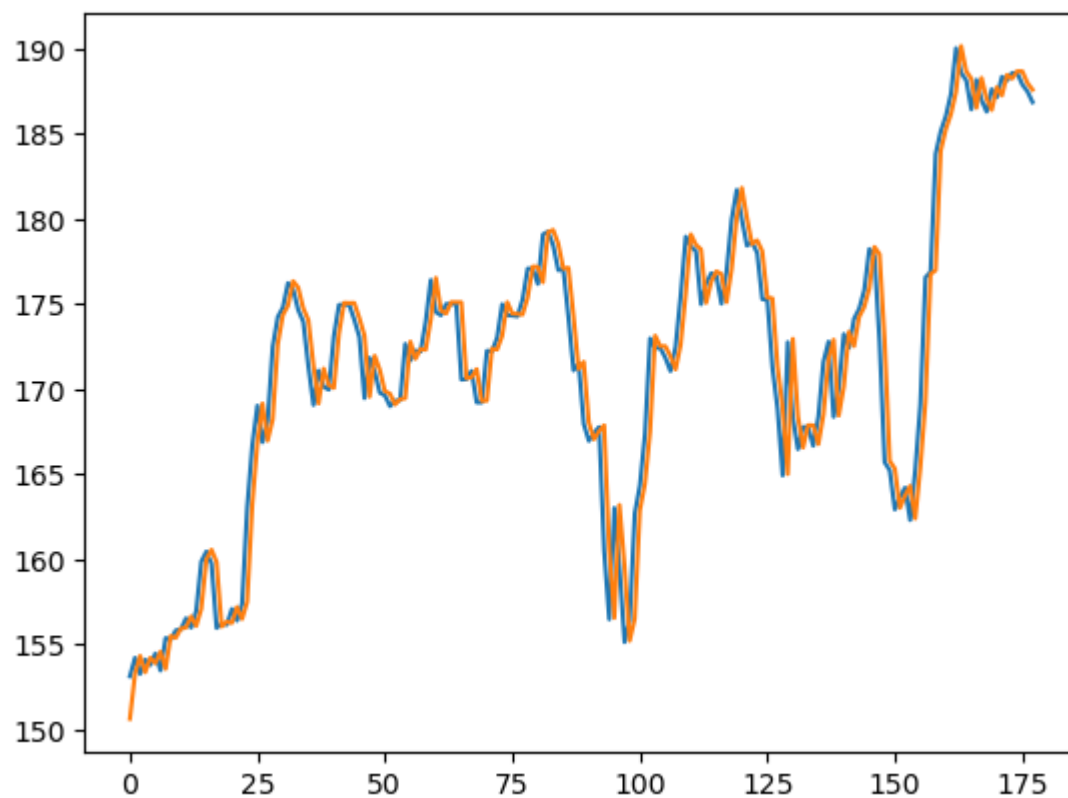
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```

```
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```

Test RMSE: 2.371



```
In [41]: # 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
gru_model = fit_gru(train_scaled, 1, 1)

# forecast
train_resaped = train_scaled[:, 0].reshape(len(train_scaled), 1, 1)
gru_model.predict(train_resaped, 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_gru(gru_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('\n Test RMSE: %.3f' % rmse)
# line plot of observed vs predicted
pyplot.plot(raw_values[-15:])
pyplot.plot(predictions)
pyplot.show()
```

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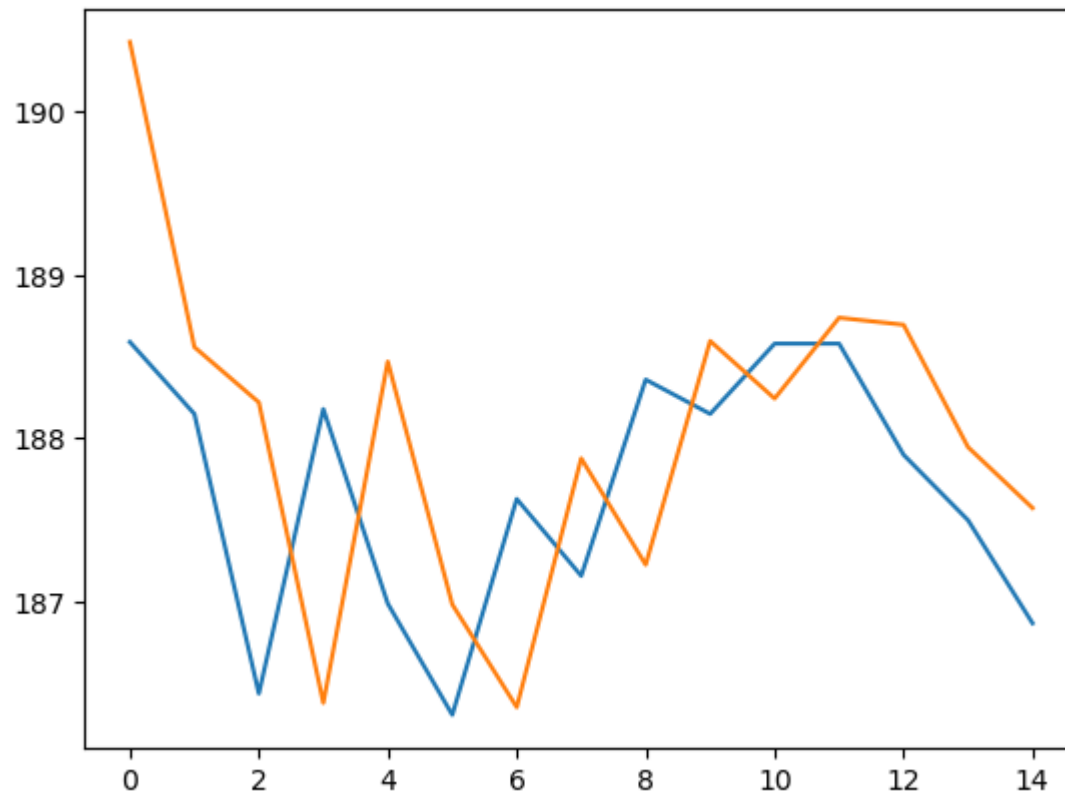
1/1 [=====] - 0s 15ms/step

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Test RMSE: 1.085



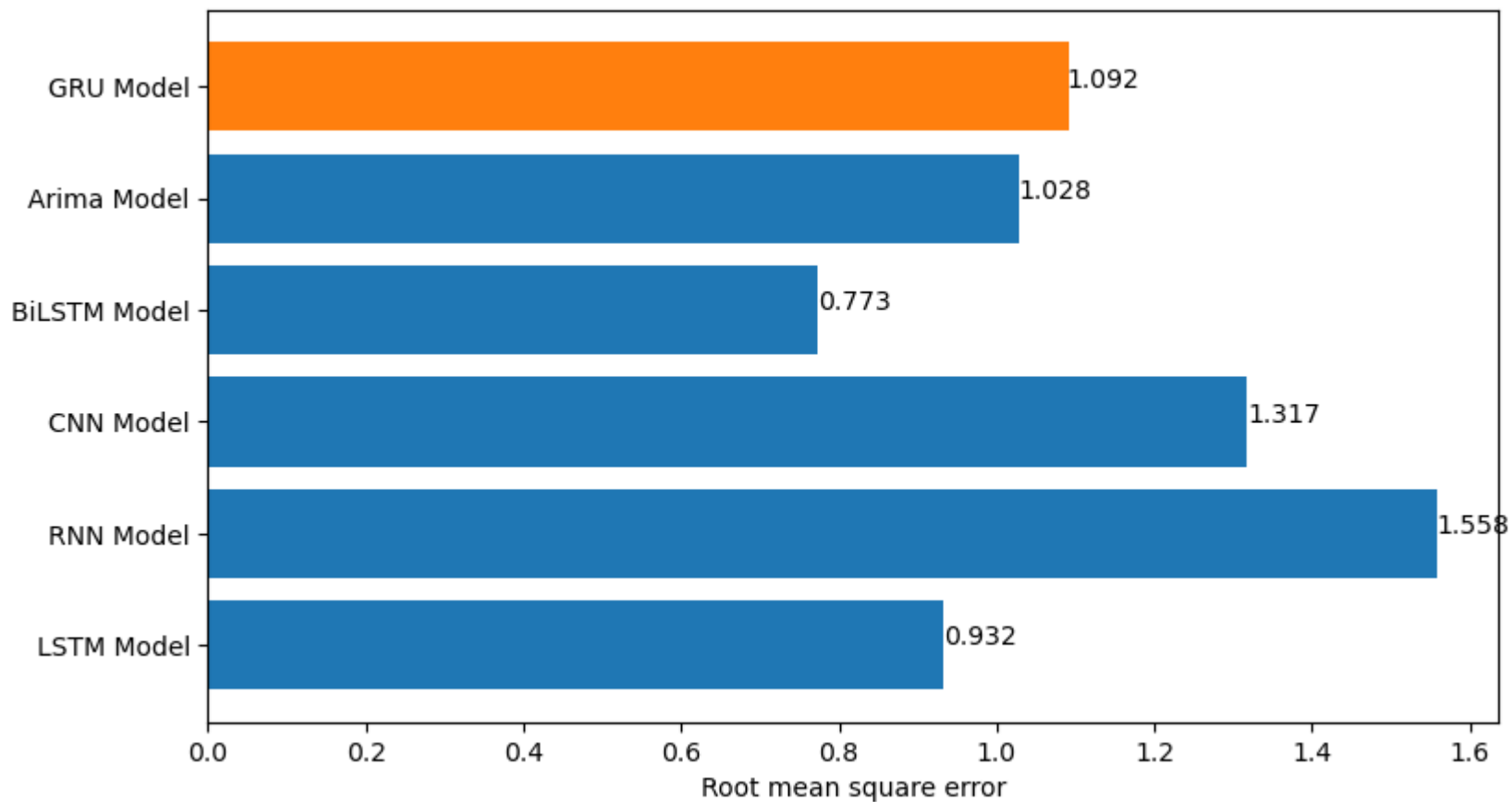
Model Comparison

```
In [42]: from matplotlib import pyplot
pyplot.figure(figsize=(9, 5))

# models
Models_used = ["LSTM Model", "RNN Model", "CNN Model", "BiLSTM Model", "Arima Model"]

# metrics of the model in list format
rmse_of_models = [0.932, 1.558, 1.317, 0.773, 1.028]
pyplot.barh(Models_used, rmse_of_models)
pyplot.barh("GRU Model", 1.092)
pyplot.xlabel("Root mean square error")
for index, value in enumerate(rmse_of_models):
    pyplot.text(value, index, str(value))
pyplot.text(1.088, 5, str(1.092))

pyplot.show()
```

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 []: