```
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense
```

Stacked LSTM

```
In [2]: file path = (r'C:\Users\begba\Desktop\praktika-master\PIB.xlsx')
         data = pd.read excel(file path)
In [3]: | scaler = MinMaxScaler(feature range=(0, 1))
         scaled_data = scaler.fit_transform(data)
In [4]: train_size = int(len(scaled data) * 0.8)
         test size = len(scaled data) - train size
         train_data, test_data = scaled_data[0:train_size,:], scaled_data[train_size:len(scaled_d
In [5]: def create dataset(dataset, time steps=1):
            X, Y = [], []
            for i in range(len(dataset)-time steps-1):
                a = dataset[i:(i+time steps), 0]
                 X.append(a)
                 Y.append(dataset[i + time steps, 0])
             return np.array(X), np.array(Y)
In [6]: time steps = 1
         X train, Y train = create dataset(train data, time steps)
         X test, Y test = create dataset(test data, time steps)
In [7]: # Reshape input to be [samples, time steps, features]
        X train = np.reshape(X train, (X train.shape[0], 1, X train.shape[1]))
         X test = np.reshape(X test, (X test.shape[0], 1, X test.shape[1]))
In [8]: model = Sequential()
         model.add(LSTM(units=50, return sequences=True, input shape=(1, time steps)))
        model.add(LSTM(units=50))
        model.add(Dense(units=1))
In [9]: model.compile(optimizer='adam', loss='mean squared error')
In [10]: | model.fit(X_train, Y_train, epochs=100, batch size=1, verbose=2)
        Epoch 1/100
        14/14 - 9s - loss: 0.1887 - 9s/epoch - 636ms/step
        Epoch 2/100
        14/14 - 0s - loss: 0.1467 - 88ms/epoch - 6ms/step
        Epoch 3/100
        14/14 - 0s - loss: 0.1053 - 81ms/epoch - 6ms/step
        Epoch 4/100
        14/14 - 0s - loss: 0.0662 - 77ms/epoch - 6ms/step
        Epoch 5/100
        14/14 - 0s - loss: 0.0463 - 86ms/epoch - 6ms/step
        Epoch 6/100
        14/14 - 0s - loss: 0.0355 - 135ms/epoch - 10ms/step
        Epoch 7/100
        14/14 - 0s - loss: 0.0331 - 71ms/epoch - 5ms/step
        Epoch 8/100
        14/14 - 0s - loss: 0.0309 - 71ms/epoch - 5ms/step
        Epoch 9/100
```

```
14/14 - 0s - loss: 0.0276 - 85ms/epoch - 6ms/step
Epoch 10/100
14/14 - 0s - loss: 0.0253 - 79ms/epoch - 6ms/step
Epoch 11/100
14/14 - 0s - loss: 0.0227 - 67ms/epoch - 5ms/step
Epoch 12/100
14/14 - 0s - loss: 0.0202 - 83ms/epoch - 6ms/step
Epoch 13/100
14/14 - 0s - loss: 0.0184 - 73ms/epoch - 5ms/step
Epoch 14/100
14/14 - 0s - loss: 0.0168 - 80ms/epoch - 6ms/step
Epoch 15/100
14/14 - 0s - loss: 0.0153 - 82ms/epoch - 6ms/step
Epoch 16/100
14/14 - 0s - loss: 0.0146 - 76ms/epoch - 5ms/step
Epoch 17/100
14/14 - 0s - loss: 0.0136 - 83ms/epoch - 6ms/step
Epoch 18/100
14/14 - 0s - loss: 0.0131 - 70ms/epoch - 5ms/step
Epoch 19/100
14/14 - 0s - loss: 0.0122 - 83ms/epoch - 6ms/step
Epoch 20/100
14/14 - 0s - loss: 0.0123 - 71ms/epoch - 5ms/step
Epoch 21/100
14/14 - 0s - loss: 0.0118 - 87ms/epoch - 6ms/step
Epoch 22/100
14/14 - 0s - loss: 0.0117 - 76ms/epoch - 5ms/step
Epoch 23/100
14/14 - 0s - loss: 0.0118 - 77ms/epoch - 5ms/step
Epoch 24/100
14/14 - 0s - loss: 0.0118 - 74ms/epoch - 5ms/step
Epoch 25/100
14/14 - 0s - loss: 0.0114 - 86ms/epoch - 6ms/step
Epoch 26/100
14/14 - 0s - loss: 0.0115 - 65ms/epoch - 5ms/step
Epoch 27/100
14/14 - 0s - loss: 0.0115 - 78ms/epoch - 6ms/step
Epoch 28/100
14/14 - 0s - loss: 0.0116 - 79ms/epoch - 6ms/step
Epoch 29/100
14/14 - 0s - loss: 0.0119 - 73ms/epoch - 5ms/step
Epoch 30/100
14/14 - 0s - loss: 0.0118 - 81ms/epoch - 6ms/step
Epoch 31/100
14/14 - 0s - loss: 0.0116 - 79ms/epoch - 6ms/step
Epoch 32/100
14/14 - 0s - loss: 0.0121 - 78ms/epoch - 6ms/step
Epoch 33/100
14/14 - 0s - loss: 0.0116 - 81ms/epoch - 6ms/step
Epoch 34/100
14/14 - 0s - loss: 0.0118 - 72ms/epoch - 5ms/step
Epoch 35/100
14/14 - 0s - loss: 0.0115 - 80ms/epoch - 6ms/step
Epoch 36/100
14/14 - 0s - loss: 0.0115 - 71ms/epoch - 5ms/step
Epoch 37/100
14/14 - 0s - loss: 0.0113 - 73ms/epoch - 5ms/step
Epoch 38/100
14/14 - 0s - loss: 0.0119 - 75ms/epoch - 5ms/step
Epoch 39/100
14/14 - 0s - loss: 0.0112 - 71ms/epoch - 5ms/step
Epoch 40/100
14/14 - 0s - loss: 0.0117 - 85ms/epoch - 6ms/step
Epoch 41/100
14/14 - 0s - loss: 0.0113 - 78ms/epoch - 6ms/step
```

Epoch 42/100

```
14/14 - 0s - loss: 0.0115 - 77ms/epoch - 6ms/step
Epoch 43/100
14/14 - 0s - loss: 0.0115 - 87ms/epoch - 6ms/step
Epoch 44/100
14/14 - 0s - loss: 0.0113 - 65ms/epoch - 5ms/step
Epoch 45/100
14/14 - 0s - loss: 0.0118 - 87ms/epoch - 6ms/step
Epoch 46/100
14/14 - 0s - loss: 0.0112 - 69ms/epoch - 5ms/step
Epoch 47/100
14/14 - 0s - loss: 0.0111 - 88ms/epoch - 6ms/step
Epoch 48/100
14/14 - 0s - loss: 0.0113 - 80ms/epoch - 6ms/step
Epoch 49/100
14/14 - 0s - loss: 0.0111 - 68ms/epoch - 5ms/step
Epoch 50/100
14/14 - 0s - loss: 0.0111 - 83ms/epoch - 6ms/step
Epoch 51/100
14/14 - 0s - loss: 0.0112 - 69ms/epoch - 5ms/step
Epoch 52/100
14/14 - 0s - loss: 0.0113 - 79ms/epoch - 6ms/step
Epoch 53/100
14/14 - 0s - loss: 0.0113 - 80ms/epoch - 6ms/step
Epoch 54/100
14/14 - 0s - loss: 0.0113 - 87ms/epoch - 6ms/step
Epoch 55/100
14/14 - 0s - loss: 0.0113 - 87ms/epoch - 6ms/step
Epoch 56/100
14/14 - 0s - loss: 0.0116 - 119ms/epoch - 8ms/step
Epoch 57/100
14/14 - 0s - loss: 0.0111 - 87ms/epoch - 6ms/step
Epoch 58/100
14/14 - 0s - loss: 0.0113 - 77ms/epoch - 6ms/step
Epoch 59/100
14/14 - 0s - loss: 0.0110 - 69ms/epoch - 5ms/step
Epoch 60/100
14/14 - 0s - loss: 0.0111 - 79ms/epoch - 6ms/step
Epoch 61/100
14/14 - 0s - loss: 0.0111 - 79ms/epoch - 6ms/step
Epoch 62/100
14/14 - 0s - loss: 0.0115 - 74ms/epoch - 5ms/step
Epoch 63/100
14/14 - 0s - loss: 0.0112 - 69ms/epoch - 5ms/step
Epoch 64/100
14/14 - 0s - loss: 0.0111 - 81ms/epoch - 6ms/step
Epoch 65/100
14/14 - 0s - loss: 0.0114 - 76ms/epoch - 5ms/step
Epoch 66/100
14/14 - 0s - loss: 0.0110 - 73ms/epoch - 5ms/step
Epoch 67/100
14/14 - 0s - loss: 0.0114 - 75ms/epoch - 5ms/step
Epoch 68/100
14/14 - 0s - loss: 0.0112 - 69ms/epoch - 5ms/step
Epoch 69/100
14/14 - 0s - loss: 0.0111 - 87ms/epoch - 6ms/step
Epoch 70/100
14/14 - 0s - loss: 0.0113 - 80ms/epoch - 6ms/step
Epoch 71/100
14/14 - 0s - loss: 0.0110 - 78ms/epoch - 6ms/step
Epoch 72/100
14/14 - 0s - loss: 0.0123 - 80ms/epoch - 6ms/step
Epoch 73/100
14/14 - 0s - loss: 0.0121 - 74ms/epoch - 5ms/step
Epoch 74/100
14/14 - 0s - loss: 0.0123 - 74ms/epoch - 5ms/step
```

Epoch 75/100

```
14/14 - 0s - loss: 0.0116 - 77ms/epoch - 5ms/step
        Epoch 76/100
        14/14 - 0s - loss: 0.0115 - 72ms/epoch - 5ms/step
        Epoch 77/100
        14/14 - 0s - loss: 0.0110 - 83ms/epoch - 6ms/step
        Epoch 78/100
        14/14 - 0s - loss: 0.0112 - 66ms/epoch - 5ms/step
        Epoch 79/100
        14/14 - 0s - loss: 0.0113 - 80ms/epoch - 6ms/step
        Epoch 80/100
        14/14 - 0s - loss: 0.0111 - 77ms/epoch - 5ms/step
        Epoch 81/100
        14/14 - 0s - loss: 0.0115 - 67ms/epoch - 5ms/step
        Epoch 82/100
        14/14 - 0s - loss: 0.0114 - 72ms/epoch - 5ms/step
        Epoch 83/100
        14/14 - 0s - loss: 0.0107 - 75ms/epoch - 5ms/step
        Epoch 84/100
        14/14 - 0s - loss: 0.0109 - 73ms/epoch - 5ms/step
        Epoch 85/100
        14/14 - 0s - loss: 0.0117 - 68ms/epoch - 5ms/step
        Epoch 86/100
        14/14 - 0s - loss: 0.0115 - 80ms/epoch - 6ms/step
        Epoch 87/100
        14/14 - 0s - loss: 0.0109 - 129ms/epoch - 9ms/step
        Epoch 88/100
        14/14 - 0s - loss: 0.0112 - 71ms/epoch - 5ms/step
        Epoch 89/100
        14/14 - 0s - loss: 0.0119 - 75ms/epoch - 5ms/step
        Epoch 90/100
        14/14 - 0s - loss: 0.0119 - 82ms/epoch - 6ms/step
        Epoch 91/100
        14/14 - 0s - loss: 0.0112 - 80ms/epoch - 6ms/step
        Epoch 92/100
        14/14 - 0s - loss: 0.0116 - 77ms/epoch - 6ms/step
        Epoch 93/100
        14/14 - 0s - loss: 0.0109 - 73ms/epoch - 5ms/step
        Epoch 94/100
        14/14 - 0s - loss: 0.0110 - 76ms/epoch - 5ms/step
        Epoch 95/100
        14/14 - 0s - loss: 0.0108 - 80ms/epoch - 6ms/step
        Epoch 96/100
        14/14 - 0s - loss: 0.0115 - 75ms/epoch - 5ms/step
        Epoch 97/100
        14/14 - 0s - loss: 0.0111 - 74ms/epoch - 5ms/step
        Epoch 98/100
        14/14 - 0s - loss: 0.0108 - 72ms/epoch - 5ms/step
        Epoch 99/100
        14/14 - 0s - loss: 0.0114 - 79ms/epoch - 6ms/step
        Epoch 100/100
        14/14 - 0s - loss: 0.0109 - 80ms/epoch - 6ms/step
        <keras.callbacks.History at 0x20f5adeeaf0>
Out[10]:
         # predictions array with shape (2,1)
In [11]:
        predictions = np.array([[1], [2]])
         expanded predictions = np.repeat(predictions, 3, axis=1)
         # Now, expanded predictions has shape (2, 3), which matches the expected input shape for
         try:
            inverse transformed predictions = scaler.inverse transform(expanded predictions)
            print(inverse transformed predictions)
         except Exception as e:
            print(f"Error during inverse transformation: {e}")
```

```
[[2.023000e+03 4.000000e+00 4.159069e+05]
[2.027000e+03 7.000000e+00 5.917351e+05]]
```

Vanilla LSTM

```
data.head()
In [13]:
Out[13]:
           Anul Trimestrul
                              PIB
         0 2019
                       1 252368.6
         1 2019
                       2 262370.8
         2 2019
                       3 267966.3
         3 2019
                       4 276961.0
         4 2020
                       1 272031.8
In [14]: | scaler = MinMaxScaler(feature range=(0, 1))
         data['PIB'] = scaler.fit transform(data[['PIB']])
In [15]: def create_sequences(data, sequence length):
            X, y = [], []
             for i in range(len(data) - sequence length):
                 X.append(data[i:i+sequence length])
                 y.append(data[i+sequence length])
             return np.array(X), np.array(y)
         sequence length = 3
         X, y = create sequences(data['PIB'].values, sequence length)
In [16]: print("Shape of X before reshaping:", X.shape)
         if len(X.shape) == 2:
             X = X.reshape((X.shape[0], X.shape[1], 1))
         print("Shape of X after reshaping:", X.shape)
         model = Sequential()
         model.add(LSTM(units=50, input shape=(X.shape[1], X.shape[2])))
         model.add(Dense(units=1))
         model.compile(optimizer='adam', loss='mean squared error')
         Shape of X before reshaping: (17, 3)
         Shape of X after reshaping: (17, 3, 1)
In [17]:
         model = Sequential()
         model.add(LSTM(units=50, input_shape=(X.shape[1], X.shape[2])))
         model.add(Dense(units=1))
         model.compile(optimizer='adam', loss='mean squared error')
In [18]: history = model.fit(X, y, epochs=100, batch size=1, verbose=2)
         Epoch 1/100
         17/17 - 4s - loss: 0.1996 - 4s/epoch - 211ms/step
         Epoch 2/100
         17/17 - 0s - loss: 0.0827 - 83ms/epoch - 5ms/step
         Epoch 3/100
         17/17 - 0s - loss: 0.0272 - 80ms/epoch - 5ms/step
         Epoch 4/100
```

17/17 - 0s - loss: 0.0224 - 82ms/epoch - 5ms/step

```
Epoch 5/100
17/17 - 0s - loss: 0.0179 - 86ms/epoch - 5ms/step
Epoch 6/100
17/17 - 0s - loss: 0.0165 - 77ms/epoch - 5ms/step
Epoch 7/100
17/17 - 0s - loss: 0.0131 - 87ms/epoch - 5ms/step
Epoch 8/100
17/17 - 0s - loss: 0.0113 - 81ms/epoch - 5ms/step
Epoch 9/100
17/17 - 0s - loss: 0.0097 - 88ms/epoch - 5ms/step
Epoch 10/100
17/17 - 0s - loss: 0.0094 - 79ms/epoch - 5ms/step
Epoch 11/100
17/17 - 0s - loss: 0.0082 - 88ms/epoch - 5ms/step
Epoch 12/100
17/17 - 0s - loss: 0.0080 - 81ms/epoch - 5ms/step
Epoch 13/100
17/17 - 0s - loss: 0.0075 - 81ms/epoch - 5ms/step
Epoch 14/100
17/17 - 0s - loss: 0.0073 - 82ms/epoch - 5ms/step
Epoch 15/100
17/17 - 0s - loss: 0.0075 - 80ms/epoch - 5ms/step
Epoch 16/100
17/17 - 0s - loss: 0.0074 - 80ms/epoch - 5ms/step
Epoch 17/100
17/17 - 0s - loss: 0.0071 - 83ms/epoch - 5ms/step
Epoch 18/100
17/17 - 0s - loss: 0.0073 - 80ms/epoch - 5ms/step
Epoch 19/100
17/17 - 0s - loss: 0.0072 - 78ms/epoch - 5ms/step
Epoch 20/100
17/17 - 0s - loss: 0.0072 - 98ms/epoch - 6ms/step
Epoch 21/100
17/17 - 0s - loss: 0.0072 - 80ms/epoch - 5ms/step
Epoch 22/100
17/17 - 0s - loss: 0.0076 - 85ms/epoch - 5ms/step
Epoch 23/100
17/17 - 0s - loss: 0.0078 - 81ms/epoch - 5ms/step
Epoch 24/100
17/17 - 0s - loss: 0.0078 - 83ms/epoch - 5ms/step
Epoch 25/100
17/17 - 0s - loss: 0.0073 - 79ms/epoch - 5ms/step
Epoch 26/100
17/17 - 0s - loss: 0.0070 - 88ms/epoch - 5ms/step
Epoch 27/100
17/17 - 0s - loss: 0.0070 - 70ms/epoch - 4ms/step
Epoch 28/100
17/17 - 0s - loss: 0.0071 - 89ms/epoch - 5ms/step
Epoch 29/100
17/17 - 0s - loss: 0.0072 - 70ms/epoch - 4ms/step
Epoch 30/100
17/17 - 0s - loss: 0.0069 - 84ms/epoch - 5ms/step
Epoch 31/100
17/17 - 0s - loss: 0.0075 - 79ms/epoch - 5ms/step
Epoch 32/100
17/17 - 0s - loss: 0.0068 - 82ms/epoch - 5ms/step
Epoch 33/100
17/17 - 0s - loss: 0.0074 - 87ms/epoch - 5ms/step
Epoch 34/100
17/17 - 0s - loss: 0.0072 - 73ms/epoch - 4ms/step
Epoch 35/100
17/17 - 0s - loss: 0.0070 - 83ms/epoch - 5ms/step
Epoch 36/100
17/17 - 0s - loss: 0.0069 - 70ms/epoch - 4ms/step
Epoch 37/100
```

17/17 - 0s - loss: 0.0070 - 74ms/epoch - 4ms/step

```
Epoch 38/100
17/17 - 0s - loss: 0.0073 - 76ms/epoch - 4ms/step
Epoch 39/100
17/17 - 0s - loss: 0.0068 - 84ms/epoch - 5ms/step
Epoch 40/100
17/17 - 0s - loss: 0.0076 - 80ms/epoch - 5ms/step
Epoch 41/100
17/17 - 0s - loss: 0.0068 - 87ms/epoch - 5ms/step
Epoch 42/100
17/17 - 0s - loss: 0.0073 - 76ms/epoch - 4ms/step
Epoch 43/100
17/17 - 0s - loss: 0.0077 - 85ms/epoch - 5ms/step
Epoch 44/100
17/17 - 0s - loss: 0.0065 - 86ms/epoch - 5ms/step
Epoch 45/100
17/17 - 0s - loss: 0.0070 - 84ms/epoch - 5ms/step
Epoch 46/100
17/17 - 0s - loss: 0.0071 - 106ms/epoch - 6ms/step
Epoch 47/100
17/17 - 0s - loss: 0.0071 - 88ms/epoch - 5ms/step
Epoch 48/100
17/17 - 0s - loss: 0.0072 - 80ms/epoch - 5ms/step
Epoch 49/100
17/17 - 0s - loss: 0.0067 - 95ms/epoch - 6ms/step
Epoch 50/100
17/17 - 0s - loss: 0.0069 - 85ms/epoch - 5ms/step
Epoch 51/100
17/17 - 0s - loss: 0.0069 - 85ms/epoch - 5ms/step
Epoch 52/100
17/17 - 0s - loss: 0.0070 - 101ms/epoch - 6ms/step
Epoch 53/100
17/17 - 0s - loss: 0.0075 - 131ms/epoch - 8ms/step
Epoch 54/100
17/17 - 0s - loss: 0.0074 - 86ms/epoch - 5ms/step
Epoch 55/100
17/17 - 0s - loss: 0.0075 - 103ms/epoch - 6ms/step
Epoch 56/100
17/17 - 0s - loss: 0.0068 - 123ms/epoch - 7ms/step
Epoch 57/100
17/17 - 0s - loss: 0.0066 - 102ms/epoch - 6ms/step
Epoch 58/100
17/17 - 0s - loss: 0.0070 - 107ms/epoch - 6ms/step
Epoch 59/100
17/17 - 0s - loss: 0.0066 - 77ms/epoch - 5ms/step
Epoch 60/100
17/17 - 0s - loss: 0.0069 - 76ms/epoch - 4ms/step
Epoch 61/100
17/17 - 0s - loss: 0.0065 - 90ms/epoch - 5ms/step
Epoch 62/100
17/17 - 0s - loss: 0.0071 - 95ms/epoch - 6ms/step
Epoch 63/100
17/17 - 0s - loss: 0.0072 - 88ms/epoch - 5ms/step
Epoch 64/100
17/17 - 0s - loss: 0.0068 - 87ms/epoch - 5ms/step
Epoch 65/100
17/17 - 0s - loss: 0.0068 - 78ms/epoch - 5ms/step
Epoch 66/100
17/17 - 0s - loss: 0.0066 - 82ms/epoch - 5ms/step
Epoch 67/100
17/17 - 0s - loss: 0.0067 - 134ms/epoch - 8ms/step
Epoch 68/100
17/17 - 0s - loss: 0.0070 - 107ms/epoch - 6ms/step
Epoch 69/100
17/17 - 0s - loss: 0.0069 - 92ms/epoch - 5ms/step
Epoch 70/100
```

17/17 - 0s - loss: 0.0080 - 78ms/epoch - 5ms/step

```
Epoch 71/100
17/17 - 0s - loss: 0.0067 - 92ms/epoch - 5ms/step
Epoch 72/100
17/17 - 0s - loss: 0.0068 - 142ms/epoch - 8ms/step
Epoch 73/100
17/17 - 0s - loss: 0.0062 - 117ms/epoch - 7ms/step
Epoch 74/100
17/17 - 0s - loss: 0.0067 - 121ms/epoch - 7ms/step
Epoch 75/100
17/17 - 0s - loss: 0.0068 - 90ms/epoch - 5ms/step
Epoch 76/100
17/17 - 0s - loss: 0.0064 - 87ms/epoch - 5ms/step
Epoch 77/100
17/17 - 0s - loss: 0.0063 - 74ms/epoch - 4ms/step
Epoch 78/100
17/17 - 0s - loss: 0.0064 - 96ms/epoch - 6ms/step
Epoch 79/100
17/17 - 0s - loss: 0.0065 - 88ms/epoch - 5ms/step
Epoch 80/100
17/17 - 0s - loss: 0.0069 - 91ms/epoch - 5ms/step
Epoch 81/100
17/17 - 0s - loss: 0.0068 - 107ms/epoch - 6ms/step
Epoch 82/100
17/17 - 0s - loss: 0.0062 - 82ms/epoch - 5ms/step
Epoch 83/100
17/17 - 0s - loss: 0.0064 - 86ms/epoch - 5ms/step
Epoch 84/100
17/17 - 0s - loss: 0.0064 - 124ms/epoch - 7ms/step
Epoch 85/100
17/17 - 0s - loss: 0.0065 - 66ms/epoch - 4ms/step
Epoch 86/100
17/17 - 0s - loss: 0.0062 - 81ms/epoch - 5ms/step
Epoch 87/100
17/17 - 0s - loss: 0.0066 - 88ms/epoch - 5ms/step
Epoch 88/100
17/17 - 0s - loss: 0.0065 - 77ms/epoch - 5ms/step
Epoch 89/100
17/17 - 0s - loss: 0.0066 - 86ms/epoch - 5ms/step
Epoch 90/100
17/17 - 0s - loss: 0.0065 - 83ms/epoch - 5ms/step
Epoch 91/100
17/17 - 0s - loss: 0.0066 - 64ms/epoch - 4ms/step
Epoch 92/100
17/17 - 0s - loss: 0.0064 - 72ms/epoch - 4ms/step
Epoch 93/100
17/17 - 0s - loss: 0.0065 - 73ms/epoch - 4ms/step
Epoch 94/100
17/17 - 0s - loss: 0.0065 - 72ms/epoch - 4ms/step
Epoch 95/100
17/17 - 0s - loss: 0.0074 - 79ms/epoch - 5ms/step
Epoch 96/100
17/17 - 0s - loss: 0.0068 - 83ms/epoch - 5ms/step
Epoch 97/100
17/17 - 0s - loss: 0.0068 - 78ms/epoch - 5ms/step
Epoch 98/100
17/17 - 0s - loss: 0.0063 - 80ms/epoch - 5ms/step
Epoch 99/100
17/17 - 0s - loss: 0.0061 - 79ms/epoch - 5ms/step
Epoch 100/100
17/17 - 0s - loss: 0.0061 - 81ms/epoch - 5ms/step
predictions = model.predict(X)
```

```
In [19]: # Make predictions
    predictions = model.predict(X)
    predictions_inverse = scaler.inverse_transform(predictions)
    y_inverse = scaler.inverse_transform(y.reshape(-1, 1))
```

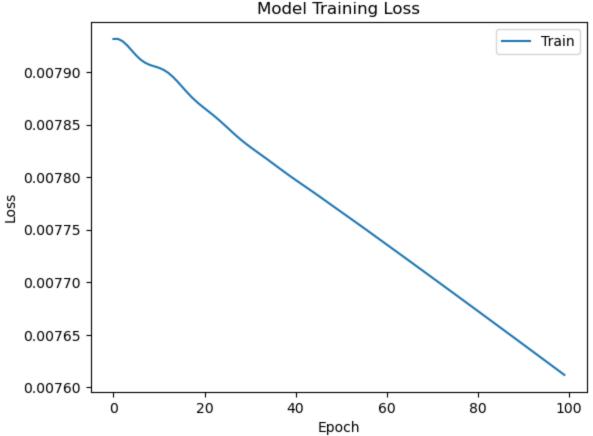
```
1/1 [=======] - 1s 971ms/step
In [20]: from sklearn.metrics import mean squared error
      rmse = np.sqrt(mean squared error(y inverse, predictions inverse))
      print("Root Mean Squared Error:", rmse)
      Root Mean Squared Error: 13474.31446350236
      Bidirectional LSTM
In [21]: from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import LSTM, Dense, Bidirectional
      import matplotlib.pyplot as plt
      from keras.models import load model
      from numpy import array
In [22]: def split_sequence(sequence, n steps):
         X, y = list(), list()
         for i in range(len(sequence)):
            #find the end of this pattern
            end ix = i + n steps
            #check if we are beyond the sequence
            if end ix > len(sequence)-1:
               #gather input and output parts of the pattern
               seq x, seq y = sequence[i:end ix], sequence[end ix]
               X.append(seq x)
               y.append(seq y)
               return array(X), array(y)
In [23]:
      #define input sequence
      raw sequence = data['PIB'].tolist()
In [24]: n_{steps} = 3
In [25]: n_features = 1
In [26]: # Adjust the input shape parameter to match data's shape
      model = Sequential([
         LSTM(units=50, return sequences=True, input shape=(3, 1)), # Adjusted to (3, 1)
         LSTM(units=50),
         Dense(1)
      ])
      # Compile model as before
      model.compile(optimizer='adam', loss='mse')
In [27]: model.fit(X, y, epochs=100, verbose=1)
      Epoch 1/100
      Epoch 2/100
      Epoch 3/100
      Epoch 4/100
      Epoch 5/100
      Epoch 6/100
      Epoch 7/100
```

1/1 [==================================		8/100		•	10 /		_	
Epoch 10/100 1/1 [===================================			-	0s	18ms/step	-	loss:	0.2223
1/1 [==================================			-	0s	23ms/step	-	loss:	0.2091
1/1	1/1 [======]	-	0s	19ms/step	-	loss:	0.1959
1/1 [===================================	1/1 [======]	-	0s	21ms/step	-	loss:	0.1826
1/1 [===================================			_	0s	22ms/step	_	loss:	0.1691
1/1 [===================================			_	0s	21ms/step	_	loss:	0.1557
Epoch 15/100 1/1 [===================================	Epoch	14/100						
Epoch 16/100 1/1 [===================================	Epoch	15/100						
Epoch 17/100 1/1 [===================================	Epoch	16/100						
Epoch 18/100 1/1 [===================================	Epoch	17/100						
Epoch 19/100 1/1 [==========] - 0s 25ms/step - loss: 0.0771 Epoch 20/100 1/1 [========] - 0s 21ms/step - loss: 0.0656 Epoch 21/100 1/1 [==============] - 0s 25ms/step - loss: 0.0549 Epoch 22/100 1/1 [==============] - 0s 19ms/step - loss: 0.0455 Epoch 23/100 1/1 [===================================			-	0s	21ms/step	-	loss:	0.1022
1/1 [===================================			-	0s	18ms/step	-	loss:	0.0894
1/1 [===================================	1/1 [======]	-	0s	25ms/step	-	loss:	0.0771
1/1 [===================================	1/1 [======]	-	0s	21ms/step	-	loss:	0.0656
1/1 [===================================			_	0s	25ms/step	_	loss:	0.0549
1/1 [===================================			_	0s	19ms/step	_	loss:	0.0455
Epoch 24/100 1/1 [===================================	Epoch	23/100						
Epoch 25/100 1/1 [===================================	Epoch	24/100						
Epoch 26/100 1/1 [===================================	Epoch	25/100						
Epoch 27/100 1/1 [===================================	Epoch	26/100						
Epoch 28/100 1/1 [===================================			-	0s	22ms/step	-	loss:	0.0253
1/1 [===================================			-	0s	21ms/step	-	loss:	0.0254
1/1 [===================================	1/1 [======]	-	0s	21ms/step	-	loss:	0.0274
1/1 [===================================	1/1 [======]	-	0s	20ms/step	-	loss:	0.0305
			-	0s	24ms/step	_	loss:	0.0338
1/1 [========			_	0s	29ms/step	_	loss:	0.0363
Epoch 32/100 1/1 [===================================			_	0s	17ms/step	_	loss:	0.0375
Epoch 33/100 1/1 [===================================	Epoch	33/100						
Epoch 34/100	Epoch	34/100						
1/1 [===========	Epoch	35/100						
1/1 [===================================			-	0s	20ms/step	-	loss:	0.0329
1/1 [========] - 0s 31ms/step - loss: 0.0299 Epoch 37/100			-	0s	31ms/step	-	loss:	0.0299
1/1 [===================================	1/1 [======]	-	0s	20ms/step	-	loss:	0.0269
1/1 [========	1/1 [======]	-	0s	18ms/step	-	loss:	0.0243
Epoch 39/100 1/1 [===================================	1/1 [=======]	-	0s	23ms/step	-	loss:	0.0222
Epoch 40/100 1/1 [===================================				0s	18ms/step	_	loss:	0.0208

Epoch 41/100						
1/1 [======] Epoch 42/100	-	0s	25ms/step	-	loss:	0.0199
1/1 [======]	-	0s	26ms/step	-	loss:	0.0194
Epoch 43/100 1/1 [=======]	_	0s	24ms/step	_	loss:	0.0193
Epoch 44/100 1/1 [======]	_	Λα	17ms/sten	_	1088.	0 0194
Epoch 45/100						
1/1 [=======] Epoch 46/100	-	0s	17ms/step	-	loss:	0.0195
1/1 [=======] Epoch 47/100	-	0s	62ms/step	-	loss:	0.0196
1/1 [======]	-	0s	14ms/step	-	loss:	0.0196
Epoch 48/100 1/1 [=======]	_	0s	17ms/step	_	loss:	0.0194
Epoch 49/100 1/1 [======]	_	Λα	19ms/stan	_	1088.	0 0191
Epoch 50/100						
1/1 [========] Epoch 51/100	_	0s	31ms/step	_	loss:	0.0185
1/1 [=======] Epoch 52/100	-	0s	20ms/step	-	loss:	0.0179
1/1 [======]	-	0s	24ms/step	-	loss:	0.0171
Epoch 53/100 1/1 [========]	_	0s	17ms/step	_	loss:	0.0163
Epoch 54/100 1/1 [======]	_	0s	24ms/step	_	loss:	0.0155
Epoch 55/100						
1/1 [======] Epoch 56/100			_			
1/1 [======] Epoch 57/100	-	0s	24ms/step	-	loss:	0.0140
1/1 [=======] Epoch 58/100	-	0s	16ms/step	-	loss:	0.0134
1/1 [======]	_	0s	27ms/step	-	loss:	0.0130
Epoch 59/100 1/1 [=======]	_	0s	25ms/step	_	loss:	0.0126
Epoch 60/100 1/1 [=======]	_	0s	21ms/sten	_	loss.	0 0124
Epoch 61/100			_			
1/1 [=======] Epoch 62/100	_	Us	26ms/step	_	loss:	0.0122
1/1 [=======] Epoch 63/100	-	0s	24ms/step	-	loss:	0.0121
1/1 [======]	-	0s	26ms/step	-	loss:	0.0119
Epoch 64/100 1/1 [=======]	_	0s	29ms/step	_	loss:	0.0117
Epoch 65/100 1/1 [========]	_	0s	26ms/step	_	loss:	0.0115
Epoch 66/100 1/1 [======]						
Epoch 67/100						
1/1 [=======] Epoch 68/100	-	0s	28ms/step	-	loss:	0.0108
1/1 [=======] Epoch 69/100	-	0s	26ms/step	-	loss:	0.0105
1/1 [======]	-	0s	19ms/step	-	loss:	0.0101
Epoch 70/100 1/1 [=======]	_	0s	36ms/step	_	loss:	0.0098
Epoch 71/100 1/1 [======]	_	0.9	25ms/step	_	loss.	0.0096
Epoch 72/100						
1/1 [======] Epoch 73/100						
1/1 [======]	-	0s	26ms/step	-	loss:	0.0092

```
Epoch 74/100
  Epoch 75/100
  Epoch 76/100
  Epoch 77/100
  Epoch 78/100
  Epoch 79/100
  Epoch 80/100
  Epoch 81/100
  Epoch 82/100
  1/1 [============== ] - 0s 20ms/step - loss: 0.0083
  Epoch 83/100
  1/1 [========= ] - Os 22ms/step - loss: 0.0082
  Epoch 84/100
  Epoch 85/100
  Epoch 86/100
  Epoch 87/100
  Epoch 88/100
  Epoch 89/100
  Epoch 90/100
  Epoch 91/100
  Epoch 92/100
  Epoch 93/100
  Epoch 94/100
  Epoch 95/100
  Epoch 96/100
  Epoch 97/100
  Epoch 98/100
  Epoch 99/100
  Epoch 100/100
  <keras.callbacks.History at 0x20f62eaf880>
Out[27]:
  # Assuming 'history' is the History object returned by model.fit()
In [28]:
  history = model.fit(X, y, epochs=100, verbose=0)
  # Plot training loss
  plt.plot(history.history['loss'])
  plt.title('Model Training Loss')
  plt.ylabel('Loss')
  plt.xlabel('Epoch')
```

```
plt.legend(['Train'], loc='upper right')
plt.show()
```



```
In [29]: last_pib_values = array([391468.3, 402454.9, 415906.9])
         n steps = 3  # Number of time steps your model was trained on
In [30]:
         n features = 1 # Number of features per time step (univariate means 1)
         x input = last pib values.reshape((1, n steps, n features))
In [31]:
        yhat = model.predict(x input, verbose=0)
In [32]: print(yhat)
         [[4.800913]]
         CNN LSTM
         import pandas as pd
In [33]:
         import numpy as np
         from keras.models import Sequential
         from keras.layers import LSTM, Dense, Flatten, TimeDistributed, Conv1D, MaxPooling1D
         from sklearn.preprocessing import MinMaxScaler
         from numpy import array
        sequence = data['PIB'].values
In [34]:
In [35]: scaler = MinMaxScaler(feature range=(0, 1))
         sequence = scaler.fit transform(sequence.reshape(-1, 1)).flatten()
         def split sequence(sequence, n steps):
In [36]:
             X, y = [], []
             for i in range(len(sequence)):
                 end ix = i + n steps
                 if end_ix > len(sequence)-1:
```

```
seq x, seq y = sequence[i:end ix], sequence[end ix]
       X.append(seq x)
       y.append(seq y)
     return array(X), array(y)
In [37]: n_steps = 4 # Timesteps per sample
   X, y = split sequence(sequence, n steps)
In [38]: n features = 1 # Features per step (univariate)
   n seq = 2 # Number of subsequences
   n steps = 2 # Steps per subsequence
   X = X.reshape((X.shape[0], n seq, n steps, n features))
In [39]: model = Sequential([
     TimeDistributed(Conv1D(filters=64, kernel size=1, activation='relu'), input shape=(N
     TimeDistributed(MaxPooling1D(pool size=2)),
     TimeDistributed(Flatten()),
     LSTM(50, activation='relu'),
     Dense(1)
   ])
   model.compile(optimizer='adam', loss='mse')
In [40]: model.fit(X, y, epochs=100, verbose=1)
   Epoch 1/100
   Epoch 2/100
   Epoch 3/100
   Epoch 4/100
   Epoch 5/100
   Epoch 6/100
   Epoch 7/100
   Epoch 8/100
   Epoch 9/100
   Epoch 10/100
   Epoch 11/100
   Epoch 12/100
   Epoch 13/100
   Epoch 14/100
   Epoch 15/100
   Epoch 16/100
   Epoch 17/100
   Epoch 18/100
   Epoch 19/100
   Epoch 20/100
```

break

1/1 []	_	0s	21ms/step - loss: 0.1715
	21/100		0	00 / 1 0 1 605
Epoch	22/100			
Epoch] 23/100			
] 24/100	-	0s	19ms/step - loss: 0.1476
	25/100	-	0s	15ms/step - loss: 0.1395
	26/100	-	0s	12ms/step - loss: 0.1314
1/1 [27/100	-	0s	15ms/step - loss: 0.1232
1/1 [28/100	-	0s	14ms/step - loss: 0.1150
1/1 [29/100	-	0s	19ms/step - loss: 0.1068
1/1 [======================================	-	0s	18ms/step - loss: 0.0987
1/1 [======]	-	0s	18ms/step - loss: 0.0907
1/1 [31/100	-	0s	27ms/step - loss: 0.0828
1/1 [32/100	-	0s	22ms/step - loss: 0.0751
1/1 [33/100 ===================================	_	0s	18ms/step - loss: 0.0676
	34/100	_	0s	20ms/step - loss: 0.0604
	35/100 ===================================	_	0s	18ms/step - loss: 0.0536
	36/100	_	0s	17ms/step - loss: 0.0472
	37/100	_	0s	18ms/step - loss: 0.0412
_	38/100	_	0s	17ms/step - loss: 0.0358
Epoch	39/100			
Epoch	40/100			-
Epoch	41/100			-
Epoch	42/100			
Epoch	43/100			_
Epoch	44/100			-
Epoch	45/100 ===================================			-
Epoch	46/100			-
Epoch	47/100			-
Epoch	48/100			-
Epoch	49/100			-
Epoch	50/100			-
Epoch	51/100			-
Epoch	52/100			-
	53/100	-	0s	25ms/step - loss: 0.0219

1/1 []	_	0s	16ms/step	_	loss:	0.0221
	54/100		0	25 / .			0 0010
Epoch	55/100						
Epoch	56/100						
Epoch	======================================						
	======================================	-	0s	33ms/step	-	loss:	0.0198
	======================================	-	0s	47ms/step	-	loss:	0.0189
	======================================	-	0s	33ms/step	-	loss:	0.0180
1/1 [======================================	-	0s	27ms/step	-	loss:	0.0171
1/1 [======================================	-	0s	63ms/step	-	loss:	0.0164
1/1 [======================================	-	0s	53ms/step	-	loss:	0.0158
1/1 [=======]	-	0s	36ms/step	-	loss:	0.0153
1/1 [64/100	_	0s	32ms/step	-	loss:	0.0150
1/1 [65/100	_	0s	32ms/step	-	loss:	0.0148
1/1 [66/100	_	0s	21ms/step	_	loss:	0.0147
	67/100	_	0s	24ms/step	_	loss:	0.0147
	68/100	_	0s	19ms/step	_	loss:	0.0147
	69/100	_	0s	40ms/step	_	loss:	0.0147
Epoch	70/100						
Epoch	71/100			_			
Epoch	72/100						
Epoch	73/100			-			
Epoch	74/100			_			
Epoch	75/100						
Epoch	76/100			_			
Epoch	77/100						
Epoch	78/100			_			
Epoch	79/100			_			
Epoch	80/100			_			
Epoch	81/100			_			
Epoch	82/100			_			
Epoch	83/100			_			
Epoch	======================================			_			
	======================================	-	0s	24ms/step	-	loss:	0.0124
1/1 [======================================	-	0s	20ms/step	-	loss:	0.0123
-							

```
Epoch 87/100
    Epoch 88/100
    Epoch 89/100
    Epoch 90/100
    Epoch 91/100
    Epoch 92/100
    Epoch 93/100
    Epoch 94/100
    Epoch 95/100
    Epoch 96/100
    Epoch 97/100
    Epoch 98/100
    Epoch 99/100
    Epoch 100/100
    <keras.callbacks.History at 0x20f698bd1c0>
Out[40]:
In [41]: | x input = sequence[-4:] # Last four entries from the sequence
     x input = scaler.transform(x input.reshape(-1, 1)).flatten() # Normalize input
     x input = x input.reshape((1, n seq, n steps, n features))
     yhat = model.predict(x input, verbose=0)
    print(yhat)
     [[1.0792195]]
    ConvLSTM
In [42]: import pandas as pd
     import numpy as np
     from keras.models import Sequential
     from keras.layers import Dense, Flatten, ConvLSTM2D
     from sklearn.preprocessing import MinMaxScaler
     from numpy import array
In [43]: | sequence = data['PIB'].values
In [44]: scaler = MinMaxScaler(feature range=(0, 1))
     sequence = scaler.fit transform(sequence.reshape(-1, 1)).flatten()
In [45]: def split sequence(sequence, n steps):
       X, y = [], []
       for i in range(len(sequence)):
         end ix = i + n steps
         if end ix > len(sequence) -1:
         seq x, seq y = sequence[i:end ix], sequence[end ix]
         X.append(seq x)
         y.append(seq y)
       return array(X), array(y)
```

```
In [46]: n steps = 4 # Timesteps per sample
   X, y = split sequence(sequence, n steps)
In [47]: n_features = 1 # Features per step (univariate)
   n seq = 2 # Number of subsequences
   n steps = 2 # Steps per subsequence
   X = X.reshape((X.shape[0], n seq, 1, n steps, n features))
In [48]: model = Sequential([
    ConvLSTM2D(filters=64, kernel size=(1,2), activation='relu', input shape=(n seq, 1,
    Flatten(),
    Dense(1)
   1)
   model.compile(optimizer='adam', loss='mse')
In [49]: model.fit(X, y, epochs=100, verbose=1)
   Epoch 1/100
   Epoch 2/100
   Epoch 3/100
   Epoch 4/100
   Epoch 5/100
   Epoch 6/100
   Epoch 7/100
   Epoch 8/100
   Epoch 9/100
   Epoch 10/100
   Epoch 11/100
   Epoch 12/100
   Epoch 13/100
   Epoch 14/100
   Epoch 15/100
   Epoch 16/100
   1/1 [============== ] - 0s 14ms/step - loss: 0.2536
   Epoch 17/100
   Epoch 18/100
   Epoch 19/100
   Epoch 20/100
   Epoch 21/100
   Epoch 22/100
   Epoch 23/100
   Epoch 24/100
```

1/1 []	-	0s	25ms/step	-	loss:	0.2150
	25/100		0	10 /			0.0000
Epoch	26/100						
Epoch	27/100						
Epoch] . 28/100						
] 29/100	-	0s	28ms/step	-	loss:	0.1939
	======================================	-	0s	29ms/step	-	loss:	0.1885
1/1 [======================================	-	0s	27ms/step	-	loss:	0.1830
1/1 [======================================	-	0s	26ms/step	-	loss:	0.1776
1/1 [======================================	-	0s	24ms/step	-	loss:	0.1721
1/1 [=======]	-	0s	24ms/step	-	loss:	0.1667
1/1 [34/100	-	0s	19ms/step	-	loss:	0.1612
1/1 [35/100	_	0s	23ms/step	_	loss:	0.1558
1/1 [36/100	_	0s	20ms/step	_	loss:	0.1504
	37/100	_	0s	20ms/step	_	loss:	0.1449
	38/100	_	0s	33ms/step	_	loss:	0.1395
	39/100	_	0s	37ms/step	_	loss:	0.1342
Epoch	40/100			_			
Epoch	41/100						
Epoch	42/100			_			
Epoch	43/100						
Epoch	44/100			-			
Epoch	45/100			-			
Epoch	46/100			_			
Epoch	47/100			_			
Epoch	48/100			_			
Epoch	49/100			_			
Epoch	50/100			_			
Epoch	51/100			_			
	======================================	-	0s	24ms/step	-	loss:	0.0747
	======================================	-	0s	24ms/step	-	loss:	0.0705
	======================================	-	0s	26ms/step	-	loss:	0.0663
1/1 [======================================	-	0s	28ms/step	-	loss:	0.0623
1/1 [======================================	-	0s	23ms/step	-	loss:	0.0585
1/1 [======================================	-	0s	21ms/step	-	loss:	0.0549
-POCII	,						

1/1 []	-	0s	27ms/step	-	loss:	0.0514
	58/100		0	0.2		7	0 0401
Epoch] . 59/100						
Epoch	60/100						
	======================================	-	0s	19ms/step	-	loss:	0.0421
] 62/100	-	0s	20ms/step	-	loss:	0.0394
1/1 [======================================	-	0s	14ms/step	-	loss:	0.0369
1/1 [======================================	-	0s	14ms/step	-	loss:	0.0347
1/1 [======================================	-	0s	19ms/step	-	loss:	0.0326
1/1 [=======]	_	0s	19ms/step	-	loss:	0.0308
1/1 [66/100	_	0s	16ms/step	-	loss:	0.0291
1/1 [67/100	_	0s	16ms/step	-	loss:	0.0277
	68/100	_	0s	18ms/step	_	loss:	0.0264
	69/100	_	0s	17ms/step	_	loss:	0.0253
	70/100	_	0s	17ms/step	_	loss:	0.0245
Epoch	71/100						
Epoch	72/100						
Epoch	73/100						
Epoch	74/100			_			
Epoch	75/100			_			
Epoch	76/100						
Epoch	77/100			-			
Epoch	78/100						
Epoch	79/100						
Epoch	80/100			_			
Epoch	81/100			_			
Epoch	82/100			_			
Epoch	83/100			_			
	84/100	-	0s	13ms/step	-	loss:	0.0216
	======================================	-	0s	17ms/step	-	loss:	0.0216
	======================================	-	0s	15ms/step	-	loss:	0.0215
	======================================	-	0s	16ms/step	-	loss:	0.0214
1/1 [======================================	-	0s	16ms/step	-	loss:	0.0213
1/1 [======================================	-	0s	25ms/step	-	loss:	0.0211
1/1 [======================================	-	0s	18ms/step	-	loss:	0.0209
-POCII							

```
Epoch 91/100
     Epoch 92/100
     Epoch 93/100
     Epoch 94/100
     Epoch 95/100
     Epoch 96/100
     Epoch 97/100
     Epoch 98/100
     Epoch 99/100
     Epoch 100/100
     <keras.callbacks.History at 0x20f5f60d370>
Out[49]:
In [51]: | x_input = sequence[-4:] # Last four entries from the sequence
     x input = scaler.transform(x input.reshape(-1, 1)).flatten() # Normalize input
     x input = x input.reshape((1, n seq, 1, n steps, n features))
     yhat = model.predict(x input, verbose=0)
     print(yhat)
     [[0.9882692]]
In [52]: # Assuming 'scaler' is your MinMaxScaler instance and 'yhat' is your prediction
     yhat original = scaler.inverse transform(yhat)
     print("Predicted GDP value:", yhat original)
     Predicted GDP value: [[0.9882692]]
     Multiple Input Series
     import pandas as pd
In [58]:
     import numpy as np
     from numpy import array, hstack
In [59]: data = pd.read excel(r'C:\Users\begba\Desktop\praktika-master\PIB Updated.xlsx')
In [60]: print(data)
       Anul Trimestrul PIB Rata angajare Cheltuielile totale
     0 2019 1 252368.6 7892464
                                           2347.00
                2 262370.8
     1 2019
                             8142162
                                           2413.05
     2 2019
                3 267966.3
                            8154113
                                           2570.57
                4 276961.0
                             8054722
     3 2019
                                           2655.71
                1 272031.8
       2020
                             7954253
                                           2551.13
     5 2020
                2 240078.7
                             7859102
                                           2439.02
                3 265918.1
     6 2020
                            7978700
                                           2680.12
                            7967302
7300644
     7 2020
                4 286616.6
                                           2813.78
                 1 283317.9
     8
       2021
                                           2813.30
                            7520145
     9 2021
                2 289048.2
                                           2848.76
     10 2021
                 3 299379.8
                            7510097
                                           3045.97
     11 2021
                4 313454.7
                            7486105
                                           3206.41
     12 2022
                1 331114.2
                             7439170
                                           3267.71
     13 2022
                2 346335.5
                                           3306.10
                             7608656
     14 2022
                 3 355617.5
                             7552003
                                           3562.13
     15 2022 4 363828.5
                         7493612
                                           3662.18
```

```
16 2023
                           1 384075.6
                                               7378396
                                                                     3702.12
        17 2023
                          2 391468.3
                                              7417382
                                                                    3675.08
        18 2023
                          3 402454.9
                                              7455072
                                                                    4024.73
        19 2023
                           4 415906.9
                                              7466183
                                                                    4135.84
In [61]: | in_seq1 = data['Rata angajare'].values
         in seq2 = data['Cheltuielile totale'].values
         out seq = data['PIB'].values
In [63]: in seq1 = in seq1.reshape((len(in seq1), 1))
         in seq2 = in seq2.reshape((len(in seq2), 1))
         out seq = out seq.reshape((len(out seq), 1))
In [64]: dataset = hstack((in_seq1, in seq2, out seq))
In [65]: n_{steps} = 3
In [66]: def split_sequences(sequences, n_steps):
             X, y = list(), list()
             for i in range(len(sequences)):
                 # Find the end of this pattern
                 end ix = i + n steps
                 # Check if we are beyond the dataset
                 if end ix > len(sequences):
                 # Gather input and output parts of the pattern
                 seq x, seq y = sequences[i:end ix, :-1], sequences[end ix-1, -1]
                 X.append(seq x)
                 y.append(seq y)
             return array(X), array(y)
In [67]: X, y = split_sequences(dataset, n steps)
        print(X.shape, y.shape)
         (18, 3, 2) (18,)
        for i in range(len(X)):
In [68]:
            print(X[i], y[i])
         [[7.892464e+06 2.347000e+03]
         [8.142162e+06 2.413050e+03]
          [8.154113e+06 2.570570e+03]] 267966.3
         [[8.142162e+06 2.413050e+03]
          [8.154113e+06 2.570570e+03]
          [8.054722e+06 2.655710e+03]] 276961.0
         [[8.154113e+06 2.570570e+03]
          [8.054722e+06 2.655710e+03]
          [7.954253e+06 2.551130e+03]] 272031.8
         [[8.054722e+06 2.655710e+03]
          [7.954253e+06 2.551130e+03]
          [7.859102e+06 2.439020e+03]] 240078.7
         [[7.954253e+06 2.551130e+03]
          [7.859102e+06 2.439020e+03]
          [7.978700e+06 2.680120e+03]] 265918.1
         [[7.859102e+06 2.439020e+03]
         [7.978700e+06 2.680120e+03]
          [7.967302e+06 2.813780e+03]] 286616.6
         [[7.978700e+06 2.680120e+03]
          [7.967302e+06 2.813780e+03]
          [7.300644e+06 2.813300e+03]] 283317.9
         [[7.967302e+06 2.813780e+03]
          [7.300644e+06 2.813300e+03]
          [7.520145e+06 2.848760e+03]] 289048.2
         [[7.300644e+06 2.813300e+03]
```

```
[7.520145e+06 2.848760e+03]
         [7.510097e+06 3.045970e+03]] 299379.8
         [[7.520145e+06 2.848760e+03]
         [7.510097e+06 3.045970e+03]
         [7.486105e+06 3.206410e+03]] 313454.7
         [[7.510097e+06 3.045970e+03]
         [7.486105e+06 3.206410e+03]
         [7.439170e+06 3.267710e+03]] 331114.2
         [[7.486105e+06 3.206410e+03]
         [7.439170e+06 3.267710e+03]
         [7.608656e+06 3.306100e+03]] 346335.5
         [[7.439170e+06 3.267710e+03]
         [7.608656e+06 3.306100e+03]
         [7.552003e+06 3.562130e+03]] 355617.5
         [[7.608656e+06 3.306100e+03]
         [7.552003e+06 3.562130e+03]
         [7.493612e+06 3.662180e+03]] 363828.5
         [[7.552003e+06 3.562130e+03]
         [7.493612e+06 3.662180e+03]
         [7.378396e+06 3.702120e+03]] 384075.6
         [[7.493612e+06 3.662180e+03]
         [7.378396e+06 3.702120e+03]
         [7.417382e+06 3.675080e+03]] 391468.3
         [[7.378396e+06 3.702120e+03]
         [7.417382e+06 3.675080e+03]
         [7.455072e+06 4.024730e+03]] 402454.9
        [[7.417382e+06 3.675080e+03]
         [7.455072e+06 4.024730e+03]
         [7.466183e+06 4.135840e+03]] 415906.9
In [69]: print(data.head())
           Anul Trimestrul PIB Rata angajare Cheltuielile totale
        0 2019
                  1 252368.6
                                            7892464
                                                                  2347.00
        1 2019
                         2 262370.8
                                                                  2413.05
                                            8142162
        2 2019
                          3 267966.3
                                                                  2570.57
                                            8154113
        3 2019
                          4 276961.0
                                            8054722
                                                                  2655.71
        4 2020
                         1 272031.8
                                            7954253
                                                                  2551.13
In [70]: from sklearn.ensemble import RandomForestRegressor
         from sklearn.metrics import mean absolute error, mean squared error
         import numpy as np
         import matplotlib.pyplot as plt
         from sklearn.model selection import train test split
In [71]: print(data.columns)
        Index(['Anul', 'Trimestrul', 'PIB', 'Rata angajare', 'Cheltuielile totale'], dtype='obje
In [72]: X = data[['Rata angajare', 'Cheltuielile totale']]
         y = data['PIB']
In [73]: X train, X test, y train, y test = train test split(X, y, test size=0.2, random state=42
In [74]: model = RandomForestRegressor(random state=42)
        model.fit(X train, y train)
Out[74]:
               RandomForestRegressor
        RandomForestRegressor(random_state=42)
In [75]: y_pred = model.predict(X test)
```

380000 - Actual Predicted 360000 - 340000 - 320000 - 280000 - 2600000 - 260000 - 260000 - 260000 - 260000 - 260000 - 260000 - 2600000 - 260000 - 260000 - 260000 - 260000 - 260000 - 260000 - 2600000 - 260000 - 260000 - 260000 - 260000 - 260000 - 260000 - 2600000 - 260000 - 260000 - 260000 - 260000 - 260000 - 260000 - 2600000 - 260000 - 260000 - 260000 - 260000 - 260000 - 260000 - 2600000 - 260000 - 260000 - 260000 - 260000 - 260000 - 260000 - 26000000 - 260000 - 260000 - 260000 - 260000 - 260000 - 260000 - 26000000 - 26000000 - 2600000 - 2600000 - 260000 - 260000 - 260000 -

1.5

2.5

3.0

2.0

0.5

0.0

1.0

In []: