DL Prac 4

April 17, 2024

1 Practical - 4

1.0.1 Problem Statement

Recurrent neural network (RNN) - Use the Google stock prices dataset and design a time series analysis and prediction system using RNN.

[1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
```

[2]:
```
data=pd.read_csv("Google_Stock_Price_Train.csv")
data
```

[2]:
```
            Date         Open         High          Low        Close  \
0     2013-01-02   357.385559   361.151062   355.959839   359.288177
1     2013-01-03   360.122742   363.600128   358.031342   359.496826
2     2013-01-04   362.313507   368.339294   361.488861   366.600616
3     2013-01-07   365.348755   367.301056   362.929504   365.001007
4     2013-01-08   365.393463   365.771027   359.874359   364.280701
…            …           …            …            …            …
1379  2018-06-25  1143.599976  1143.910034  1112.780029  1124.810059
1380  2018-06-26  1128.000000  1133.209961  1116.659058  1118.459961
1381  2018-06-27  1121.339966  1131.836060  1103.619995  1103.979980
1382  2018-06-28  1102.089966  1122.310059  1096.010010  1114.219971
1383  2018-06-29  1120.000000  1128.227051  1115.000000  1115.650024

        Adj Close   Volume
0      359.288177  5115500
1      359.496826  4666500
2      366.600616  5562800
3      365.001007  3332900
4      364.280701  3373900
…             …        …
1379  1124.810059  2157300
1380  1118.459961  1563200
1381  1103.979980  1293900
1382  1114.219971  1072400
```

```
1383  1115.650024  1315100

[1384 rows x 7 columns]
```

[3]:
```
train = data.iloc[:1260,:]
test = data.iloc[1260:,:]
```

[4]:
```
train
```

[4]:
```
            Date         Open         High          Low        Close  \
0     2013-01-02   357.385559   361.151062   355.959839   359.288177
1     2013-01-03   360.122742   363.600128   358.031342   359.496826
2     2013-01-04   362.313507   368.339294   361.488861   366.600616
3     2013-01-07   365.348755   367.301056   362.929504   365.001007
4     2013-01-08   365.393463   365.771027   359.874359   364.280701
…            …           …           …           …           …
1255  2017-12-26  1058.069946  1060.119995  1050.199951  1056.739990
1256  2017-12-27  1057.390015  1058.369995  1048.050049  1049.369995
1257  2017-12-28  1051.599976  1054.750000  1044.770020  1048.140015
1258  2017-12-29  1046.719971  1049.699951  1044.900024  1046.400024
1259  2018-01-02  1048.339966  1066.939941  1045.229980  1065.000000

        Adj Close   Volume
0      359.288177  5115500
1      359.496826  4666500
2      366.600616  5562800
3      365.001007  3332900
4      364.280701  3373900
…             …        …
1255  1056.739990   760600
1256  1049.369995  1271900
1257  1048.140015   837100
1258  1046.400024   887500
1259  1065.000000  1237600

[1260 rows x 7 columns]
```

[5]:
```
trainset = train.iloc[:,1:2].values
```

[6]:
```
trainset
```

[6]:
```
array([[ 357.385559],
       [ 360.122742],
       [ 362.313507],
       …,
       [1051.599976],
       [1046.719971],
```

```
        [1048.339966]])
```

[7]:
```
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler(feature_range = (0,1))
training_scaled = sc.fit_transform(trainset)
```

[8]:
```
training_scaled
```

[8]:
```
array([[0.01011148],
       [0.01388614],
       [0.01690727],
       …,
       [0.9674549 ],
       [0.96072522],
       [0.96295924]])
```

[9]:
```
x_train = []
y_train = []
```

[10]:
```
for i in range(60,1125):
    x_train.append(training_scaled[i-60:i, 0])
    y_train.append(training_scaled[i,0])
x_train,y_train = np.array(x_train),np.array(y_train)
```

[11]:
```
x_train.shape
```

[11]:
```
(1065, 60)
```

[12]:
```
x_train = np.reshape(x_train, (x_train.shape[0],x_train.shape[1],1))
```

[13]:
```
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout
```

[14]:
```
model = Sequential()
model.add(LSTM(units = 50,return_sequences = True,input_shape = (x_train.
 ↪shape[1],1)))
model.add(Dropout(0.2))

model.add(LSTM(units = 50,return_sequences = True))
model.add(Dropout(0.2))

model.add(LSTM(units = 50,return_sequences = True))
model.add(Dropout(0.2))

model.add(LSTM(units = 50))
model.add(Dropout(0.2))
```

```
model.add(Dense(units = 1))
```

```
C:\Users\ADMIN\anaconda3\Lib\site-packages\keras\src\layers\rnn\rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(**kwargs)
```

[15]:
```
model.compile(optimizer = 'adam',loss = 'mse', metrics = ['mae'])
```

[33]:
```
history = model.fit(x_train,y_train,epochs = 100, batch_size =␣
↪32,validation_split=0.2, verbose=1)
```

```
Epoch 1/100
27/27               3s 121ms/step -
loss: 5.5520e-04 - mae: 0.0171 - val_loss: 8.5727e-04 - val_mae: 0.0255
Epoch 2/100
27/27               3s 112ms/step -
loss: 5.5900e-04 - mae: 0.0175 - val_loss: 4.9976e-04 - val_mae: 0.0184
Epoch 3/100
27/27               3s 103ms/step -
loss: 5.1274e-04 - mae: 0.0165 - val_loss: 4.0671e-04 - val_mae: 0.0158
Epoch 4/100
27/27               3s 112ms/step -
loss: 6.0604e-04 - mae: 0.0188 - val_loss: 4.8946e-04 - val_mae: 0.0182
Epoch 5/100
27/27               3s 106ms/step -
loss: 5.1192e-04 - mae: 0.0163 - val_loss: 3.1147e-04 - val_mae: 0.0138
Epoch 6/100
27/27               3s 119ms/step -
loss: 4.3069e-04 - mae: 0.0148 - val_loss: 7.4308e-04 - val_mae: 0.0239
Epoch 7/100
27/27               3s 113ms/step -
loss: 5.6738e-04 - mae: 0.0172 - val_loss: 2.5315e-04 - val_mae: 0.0116
Epoch 8/100
27/27               3s 119ms/step -
loss: 5.8792e-04 - mae: 0.0187 - val_loss: 6.1219e-04 - val_mae: 0.0214
Epoch 9/100
27/27               3s 111ms/step -
loss: 5.2889e-04 - mae: 0.0171 - val_loss: 6.1485e-04 - val_mae: 0.0213
Epoch 10/100
27/27               3s 112ms/step -
loss: 5.3589e-04 - mae: 0.0170 - val_loss: 2.3820e-04 - val_mae: 0.0113
Epoch 11/100
27/27               5s 112ms/step -
loss: 5.0202e-04 - mae: 0.0161 - val_loss: 5.5596e-04 - val_mae: 0.0199
Epoch 12/100
```

```
27/27              3s 106ms/step -
loss: 5.6814e-04 - mae: 0.0170 - val_loss: 2.4377e-04 - val_mae: 0.0112
Epoch 13/100
27/27              5s 103ms/step -
loss: 5.0927e-04 - mae: 0.0160 - val_loss: 4.8246e-04 - val_mae: 0.0182
Epoch 14/100
27/27              3s 120ms/step -
loss: 5.0045e-04 - mae: 0.0166 - val_loss: 2.7858e-04 - val_mae: 0.0127
Epoch 15/100
27/27              3s 109ms/step -
loss: 5.5689e-04 - mae: 0.0171 - val_loss: 5.9081e-04 - val_mae: 0.0209
Epoch 16/100
27/27              5s 104ms/step -
loss: 5.1846e-04 - mae: 0.0163 - val_loss: 4.7490e-04 - val_mae: 0.0182
Epoch 17/100
27/27              3s 113ms/step -
loss: 4.2331e-04 - mae: 0.0152 - val_loss: 3.4133e-04 - val_mae: 0.0143
Epoch 18/100
27/27              3s 105ms/step -
loss: 6.2806e-04 - mae: 0.0177 - val_loss: 3.4023e-04 - val_mae: 0.0145
Epoch 19/100
27/27              5s 107ms/step -
loss: 5.2821e-04 - mae: 0.0164 - val_loss: 2.3375e-04 - val_mae: 0.0114
Epoch 20/100
27/27              3s 114ms/step -
loss: 5.2927e-04 - mae: 0.0163 - val_loss: 2.1204e-04 - val_mae: 0.0106
Epoch 21/100
27/27              5s 108ms/step -
loss: 5.5402e-04 - mae: 0.0164 - val_loss: 5.5459e-04 - val_mae: 0.0198
Epoch 22/100
27/27              3s 108ms/step -
loss: 5.3624e-04 - mae: 0.0166 - val_loss: 2.2670e-04 - val_mae: 0.0112
Epoch 23/100
27/27              3s 116ms/step -
loss: 4.9393e-04 - mae: 0.0162 - val_loss: 4.9960e-04 - val_mae: 0.0186
Epoch 24/100
27/27              5s 116ms/step -
loss: 5.1809e-04 - mae: 0.0165 - val_loss: 0.0015 - val_mae: 0.0356
Epoch 25/100
27/27              5s 119ms/step -
loss: 5.2564e-04 - mae: 0.0171 - val_loss: 2.0285e-04 - val_mae: 0.0102
Epoch 26/100
27/27              3s 116ms/step -
loss: 4.8036e-04 - mae: 0.0159 - val_loss: 0.0014 - val_mae: 0.0348
Epoch 27/100
27/27              5s 107ms/step -
loss: 5.4110e-04 - mae: 0.0166 - val_loss: 2.1494e-04 - val_mae: 0.0105
Epoch 28/100
```

```
27/27            3s 117ms/step -
loss: 5.5272e-04 - mae: 0.0168 - val_loss: 6.8676e-04 - val_mae: 0.0230
Epoch 29/100
27/27            5s 110ms/step -
loss: 4.7867e-04 - mae: 0.0162 - val_loss: 1.9796e-04 - val_mae: 0.0102
Epoch 30/100
27/27            3s 107ms/step -
loss: 5.1670e-04 - mae: 0.0164 - val_loss: 2.3728e-04 - val_mae: 0.0119
Epoch 31/100
27/27            6s 128ms/step -
loss: 4.1897e-04 - mae: 0.0152 - val_loss: 3.1936e-04 - val_mae: 0.0143
Epoch 32/100
27/27            5s 107ms/step -
loss: 4.5702e-04 - mae: 0.0156 - val_loss: 2.9796e-04 - val_mae: 0.0132
Epoch 33/100
27/27            4s 129ms/step -
loss: 4.9140e-04 - mae: 0.0160 - val_loss: 2.9333e-04 - val_mae: 0.0139
Epoch 34/100
27/27            5s 116ms/step -
loss: 4.5712e-04 - mae: 0.0156 - val_loss: 1.9855e-04 - val_mae: 0.0105
Epoch 35/100
27/27            5s 122ms/step -
loss: 5.1828e-04 - mae: 0.0168 - val_loss: 1.9451e-04 - val_mae: 0.0102
Epoch 36/100
27/27            3s 114ms/step -
loss: 5.3116e-04 - mae: 0.0173 - val_loss: 4.3942e-04 - val_mae: 0.0180
Epoch 37/100
27/27            3s 112ms/step -
loss: 4.8781e-04 - mae: 0.0168 - val_loss: 8.4581e-04 - val_mae: 0.0255
Epoch 38/100
27/27            3s 116ms/step -
loss: 4.4631e-04 - mae: 0.0160 - val_loss: 4.6365e-04 - val_mae: 0.0187
Epoch 39/100
27/27            3s 122ms/step -
loss: 5.1139e-04 - mae: 0.0165 - val_loss: 2.0634e-04 - val_mae: 0.0102
Epoch 40/100
27/27            5s 118ms/step -
loss: 4.4520e-04 - mae: 0.0161 - val_loss: 2.3022e-04 - val_mae: 0.0114
Epoch 41/100
27/27            5s 121ms/step -
loss: 5.0802e-04 - mae: 0.0165 - val_loss: 3.1788e-04 - val_mae: 0.0145
Epoch 42/100
27/27            6s 134ms/step -
loss: 4.2678e-04 - mae: 0.0146 - val_loss: 2.9706e-04 - val_mae: 0.0140
Epoch 43/100
27/27            3s 106ms/step -
loss: 3.9782e-04 - mae: 0.0147 - val_loss: 2.0592e-04 - val_mae: 0.0103
Epoch 44/100
```

```
27/27            3s 115ms/step -
loss: 5.0251e-04 - mae: 0.0154 - val_loss: 3.4692e-04 - val_mae: 0.0151
Epoch 45/100
27/27            3s 108ms/step -
loss: 5.5484e-04 - mae: 0.0169 - val_loss: 2.1912e-04 - val_mae: 0.0111
Epoch 46/100
27/27            5s 116ms/step -
loss: 4.1759e-04 - mae: 0.0153 - val_loss: 2.7737e-04 - val_mae: 0.0134
Epoch 47/100
27/27            5s 105ms/step -
loss: 4.9493e-04 - mae: 0.0156 - val_loss: 4.2943e-04 - val_mae: 0.0175
Epoch 48/100
27/27            3s 119ms/step -
loss: 4.4262e-04 - mae: 0.0158 - val_loss: 3.2346e-04 - val_mae: 0.0146
Epoch 49/100
27/27            3s 112ms/step -
loss: 3.6505e-04 - mae: 0.0143 - val_loss: 3.2931e-04 - val_mae: 0.0150
Epoch 50/100
27/27            6s 137ms/step -
loss: 4.7136e-04 - mae: 0.0153 - val_loss: 5.8060e-04 - val_mae: 0.0205
Epoch 51/100
27/27            3s 123ms/step -
loss: 4.0933e-04 - mae: 0.0147 - val_loss: 2.2243e-04 - val_mae: 0.0109
Epoch 52/100
27/27            5s 111ms/step -
loss: 5.1576e-04 - mae: 0.0168 - val_loss: 2.3474e-04 - val_mae: 0.0113
Epoch 53/100
27/27            3s 119ms/step -
loss: 4.9167e-04 - mae: 0.0153 - val_loss: 4.6407e-04 - val_mae: 0.0182
Epoch 54/100
27/27            3s 121ms/step -
loss: 4.4753e-04 - mae: 0.0155 - val_loss: 1.9874e-04 - val_mae: 0.0103
Epoch 55/100
27/27            3s 115ms/step -
loss: 5.4563e-04 - mae: 0.0179 - val_loss: 3.5117e-04 - val_mae: 0.0157
Epoch 56/100
27/27            3s 105ms/step -
loss: 4.1960e-04 - mae: 0.0152 - val_loss: 1.7708e-04 - val_mae: 0.0095
Epoch 57/100
27/27            3s 113ms/step -
loss: 4.3865e-04 - mae: 0.0150 - val_loss: 2.9222e-04 - val_mae: 0.0131
Epoch 58/100
27/27            3s 109ms/step -
loss: 4.3743e-04 - mae: 0.0146 - val_loss: 1.6467e-04 - val_mae: 0.0091
Epoch 59/100
27/27            3s 113ms/step -
loss: 4.2956e-04 - mae: 0.0151 - val_loss: 2.6801e-04 - val_mae: 0.0128
Epoch 60/100
```

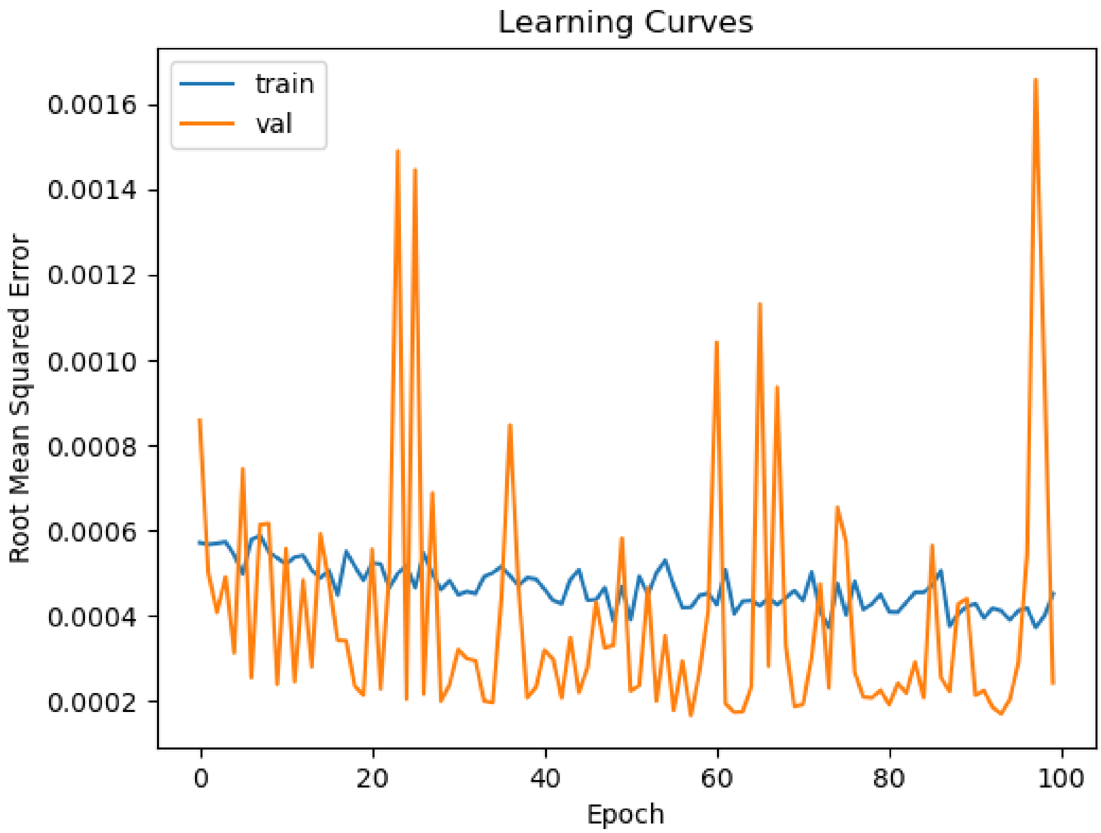
```
27/27            7s 179ms/step -
loss: 3.8432e-04 - mae: 0.0149 - val_loss: 4.1124e-04 - val_mae: 0.0172
Epoch 61/100
27/27            4s 124ms/step -
loss: 3.8596e-04 - mae: 0.0142 - val_loss: 0.0010 - val_mae: 0.0291
Epoch 62/100
27/27            4s 132ms/step -
loss: 4.9404e-04 - mae: 0.0166 - val_loss: 1.9233e-04 - val_mae: 0.0102
Epoch 63/100
27/27            4s 132ms/step -
loss: 4.0681e-04 - mae: 0.0149 - val_loss: 1.7218e-04 - val_mae: 0.0094
Epoch 64/100
27/27            5s 138ms/step -
loss: 4.4928e-04 - mae: 0.0153 - val_loss: 1.7320e-04 - val_mae: 0.0096
Epoch 65/100
27/27            4s 132ms/step -
loss: 4.1262e-04 - mae: 0.0147 - val_loss: 2.3210e-04 - val_mae: 0.0114
Epoch 66/100
27/27            3s 127ms/step -
loss: 4.3385e-04 - mae: 0.0159 - val_loss: 0.0011 - val_mae: 0.0301
Epoch 67/100
27/27            5s 115ms/step -
loss: 4.3826e-04 - mae: 0.0156 - val_loss: 2.8072e-04 - val_mae: 0.0128
Epoch 68/100
27/27            5s 114ms/step -
loss: 4.2772e-04 - mae: 0.0141 - val_loss: 9.3529e-04 - val_mae: 0.0273
Epoch 69/100
27/27            4s 127ms/step -
loss: 5.0976e-04 - mae: 0.0165 - val_loss: 3.2903e-04 - val_mae: 0.0144
Epoch 70/100
27/27            5s 138ms/step -
loss: 4.8426e-04 - mae: 0.0158 - val_loss: 1.8555e-04 - val_mae: 0.0099
Epoch 71/100
27/27            3s 120ms/step -
loss: 4.3471e-04 - mae: 0.0151 - val_loss: 1.9050e-04 - val_mae: 0.0101
Epoch 72/100
27/27            3s 124ms/step -
loss: 4.5448e-04 - mae: 0.0158 - val_loss: 2.9956e-04 - val_mae: 0.0135
Epoch 73/100
27/27            3s 120ms/step -
loss: 3.8169e-04 - mae: 0.0146 - val_loss: 4.7304e-04 - val_mae: 0.0185
Epoch 74/100
27/27            3s 108ms/step -
loss: 3.0815e-04 - mae: 0.0129 - val_loss: 2.2872e-04 - val_mae: 0.0114
Epoch 75/100
27/27            3s 120ms/step -
loss: 5.2132e-04 - mae: 0.0161 - val_loss: 6.5334e-04 - val_mae: 0.0224
Epoch 76/100
```

```
27/27            5s 119ms/step -
loss: 3.8135e-04 - mae: 0.0147 - val_loss: 5.7175e-04 - val_mae: 0.0204
Epoch 77/100
27/27            3s 118ms/step -
loss: 4.4639e-04 - mae: 0.0151 - val_loss: 2.6501e-04 - val_mae: 0.0123
Epoch 78/100
27/27            4s 131ms/step -
loss: 4.0438e-04 - mae: 0.0141 - val_loss: 2.0820e-04 - val_mae: 0.0108
Epoch 79/100
27/27            3s 115ms/step -
loss: 4.3477e-04 - mae: 0.0154 - val_loss: 2.0626e-04 - val_mae: 0.0106
Epoch 80/100
27/27            3s 112ms/step -
loss: 5.1705e-04 - mae: 0.0162 - val_loss: 2.2360e-04 - val_mae: 0.0112
Epoch 81/100
27/27            3s 109ms/step -
loss: 4.1393e-04 - mae: 0.0145 - val_loss: 1.8971e-04 - val_mae: 0.0101
Epoch 82/100
27/27            3s 105ms/step -
loss: 3.6819e-04 - mae: 0.0135 - val_loss: 2.4018e-04 - val_mae: 0.0119
Epoch 83/100
27/27            4s 130ms/step -
loss: 4.6311e-04 - mae: 0.0155 - val_loss: 2.1699e-04 - val_mae: 0.0111
Epoch 84/100
27/27            3s 108ms/step -
loss: 3.7414e-04 - mae: 0.0137 - val_loss: 2.8972e-04 - val_mae: 0.0136
Epoch 85/100
27/27            7s 169ms/step -
loss: 4.7029e-04 - mae: 0.0157 - val_loss: 2.0689e-04 - val_mae: 0.0108
Epoch 86/100
27/27            3s 126ms/step -
loss: 4.4960e-04 - mae: 0.0155 - val_loss: 5.6369e-04 - val_mae: 0.0206
Epoch 87/100
27/27            6s 156ms/step -
loss: 4.7601e-04 - mae: 0.0161 - val_loss: 2.5368e-04 - val_mae: 0.0120
Epoch 88/100
27/27            5s 150ms/step -
loss: 3.7251e-04 - mae: 0.0144 - val_loss: 2.2133e-04 - val_mae: 0.0114
Epoch 89/100
27/27            4s 134ms/step -
loss: 4.2799e-04 - mae: 0.0142 - val_loss: 4.2618e-04 - val_mae: 0.0170
Epoch 90/100
27/27            3s 121ms/step -
loss: 4.2007e-04 - mae: 0.0145 - val_loss: 4.3880e-04 - val_mae: 0.0176
Epoch 91/100
27/27            3s 123ms/step -
loss: 4.1244e-04 - mae: 0.0149 - val_loss: 2.1216e-04 - val_mae: 0.0110
Epoch 92/100
```

```
27/27 5s 123ms/step -
loss: 3.1074e-04 - mae: 0.0131 - val_loss: 2.2307e-04 - val_mae: 0.0111
Epoch 93/100
27/27 5s 117ms/step -
loss: 4.4267e-04 - mae: 0.0145 - val_loss: 1.8364e-04 - val_mae: 0.0099
Epoch 94/100
27/27 3s 126ms/step -
loss: 4.2152e-04 - mae: 0.0151 - val_loss: 1.6813e-04 - val_mae: 0.0093
Epoch 95/100
27/27 5s 126ms/step -
loss: 3.5575e-04 - mae: 0.0137 - val_loss: 2.0205e-04 - val_mae: 0.0108
Epoch 96/100
27/27 3s 121ms/step -
loss: 4.4858e-04 - mae: 0.0152 - val_loss: 2.8950e-04 - val_mae: 0.0128
Epoch 97/100
27/27 3s 128ms/step -
loss: 4.4938e-04 - mae: 0.0147 - val_loss: 5.4230e-04 - val_mae: 0.0193
Epoch 98/100
27/27 5s 123ms/step -
loss: 3.7016e-04 - mae: 0.0138 - val_loss: 0.0017 - val_mae: 0.0372
Epoch 99/100
27/27 6s 141ms/step -
loss: 4.1830e-04 - mae: 0.0147 - val_loss: 9.7377e-04 - val_mae: 0.0275
Epoch 100/100
27/27 5s 124ms/step -
loss: 4.3870e-04 - mae: 0.0152 - val_loss: 2.4154e-04 - val_mae: 0.0116
```

[34]:

```python
from matplotlib import pyplot
# plot learning curves
pyplot.title('Learning Curves')
pyplot.xlabel('Epoch')
pyplot.ylabel('Root Mean Squared Error')
pyplot.plot(history.history['loss'], label='train')
pyplot.plot(history.history['val_loss'], label='val')
pyplot.legend()
pyplot.show()
```



[35]:
```
test
```

[35]:
```
            Date         Open         High          Low        Close  \
1260  2018-01-03  1064.310059  1086.290039  1063.209961  1082.479980
1261  2018-01-04  1088.000000  1093.569946  1084.001953  1086.400024
1262  2018-01-05  1094.000000  1104.250000  1092.000000  1102.229980
1263  2018-01-08  1102.229980  1111.270020  1101.619995  1106.939941
1264  2018-01-09  1109.400024  1110.569946  1101.230957  1106.260010
…            …            …            …            …            …
1379  2018-06-25  1143.599976  1143.910034  1112.780029  1124.810059
1380  2018-06-26  1128.000000  1133.209961  1116.659058  1118.459961
1381  2018-06-27  1121.339966  1131.836060  1103.619995  1103.979980
1382  2018-06-28  1102.089966  1122.310059  1096.010010  1114.219971
1383  2018-06-29  1120.000000  1128.227051  1115.000000  1115.650024

        Adj Close   Volume
1260  1082.479980  1430200
1261  1086.400024  1004600
1262  1102.229980  1279100
1263  1106.939941  1047600
```

```
1264  1106.260010   902500
…           …        …
1379  1124.810059  2157300
1380  1118.459961  1563200
1381  1103.979980  1293900
1382  1114.219971  1072400
1383  1115.650024  1315100

[124 rows x 7 columns]
```

[36]:
```
real_stock_price = test.iloc[:,1:2].values
```

[37]:
```
dataset_total = pd.concat((train['Open'],test['Open']),axis = 0)
dataset_total
```

[37]:
```
0        357.385559
1        360.122742
2        362.313507
3        365.348755
4        365.393463
            …
1379    1143.599976
1380    1128.000000
1381    1121.339966
1382    1102.089966
1383    1120.000000
Name: Open, Length: 1384, dtype: float64
```

[38]:
```
inputs = dataset_total[len(dataset_total) - len(test)-60:].values
inputs
```

[38]:
```
array([ 966.700012,  980.      ,  980.      ,  973.719971,  987.450012,
        992.      ,  992.099976,  990.289978,  991.77002 ,  986.      ,
        989.440002,  989.52002 ,  970.      ,  968.369995,  980.      ,
       1009.190002, 1014.      , 1015.219971, 1017.210022, 1021.76001 ,
       1022.109985, 1028.98999 , 1027.27002 , 1030.52002 , 1033.98999 ,
       1026.459961, 1023.419983, 1022.590027, 1019.210022, 1022.52002 ,
       1034.01001 , 1020.26001 , 1023.309998, 1035.      , 1035.869995,
       1040.      , 1055.089966, 1042.680054, 1022.369995, 1015.799988,
       1012.659973,  995.940002, 1001.5     , 1020.429993, 1037.48999 ,
       1035.5     , 1039.630005, 1046.119995, 1045.      , 1054.609985,
       1066.079956, 1075.199951, 1071.780029, 1064.949951, 1061.109985,
       1058.069946, 1057.390015, 1051.599976, 1046.719971, 1048.339966,
       1064.310059, 1088.      , 1094.      , 1102.22998 , 1109.400024,
       1097.099976, 1106.300049, 1102.410034, 1132.51001 , 1126.219971,
       1131.410034, 1131.829956, 1137.48999 , 1159.849976, 1177.329956,
       1172.530029, 1175.079956, 1176.47998 , 1167.829956, 1170.569946,
```

```
       1162.609985, 1122.      , 1090.599976, 1027.180054, 1081.540039,
       1055.410034, 1017.25    , 1048.      , 1045.      , 1048.949951,
       1079.069946, 1088.410034, 1090.569946, 1106.469971, 1116.189941,
       1112.640015, 1127.800049, 1141.23999 , 1123.030029, 1107.869995,
       1053.079956, 1075.140015, 1099.219971, 1089.189941, 1115.319946,
       1136.      , 1163.849976, 1170.      , 1145.209961, 1149.959961,
       1154.140015, 1120.01001 , 1099.      , 1092.73999 , 1081.880005,
       1047.030029, 1046.      , 1063.      ,  998.      , 1011.630005,
       1022.820007, 1013.909973,  993.409973, 1041.329956, 1020.      ,
       1016.799988, 1026.439941, 1027.98999 , 1025.040039, 1040.880005,
       1037.      , 1051.369995, 1077.430054, 1069.400024, 1082.      ,
       1077.859985, 1052.      , 1025.52002 , 1029.51001 , 1046.      ,
       1030.01001 , 1013.659973, 1028.099976, 1019.      , 1016.900024,
       1049.22998 , 1058.540039, 1058.099976, 1086.030029, 1093.599976,
       1100.      , 1090.      , 1077.310059, 1079.890015, 1061.859985,
       1074.060059, 1083.560059, 1065.130005, 1079.      , 1079.02002 ,
       1064.890015, 1063.030029, 1067.560059, 1099.349976, 1122.329956,
       1140.98999 , 1142.170044, 1131.319946, 1118.180054, 1118.599976,
       1131.069946, 1141.119995, 1143.849976, 1148.859985, 1143.650024,
       1158.5     , 1175.310059, 1174.849976, 1159.140015, 1143.599976,
       1128.      , 1121.339966, 1102.089966, 1120.      ])
```

[39]:
```
inputs = inputs.reshape(-1,1)
```

[40]:
```
inputs
```

[40]:
```
array([[ 966.700012],
       [ 980.      ],
       [ 980.      ],
       [ 973.719971],
       [ 987.450012],
       [ 992.      ],
       [ 992.099976],
       [ 990.289978],
       [ 991.77002 ],
       [ 986.      ],
       [ 989.440002],
       [ 989.52002 ],
       [ 970.      ],
       [ 968.369995],
       [ 980.      ],
       [1009.190002],
       [1014.      ],
       [1015.219971],
       [1017.210022],
       [1021.76001 ],
       [1022.109985],
```

```
[1028.98999 ],
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[1030.52002 ],
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[1022.590027],
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[1055.089966],
[1042.680054],
[1022.369995],
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[1012.659973],
[ 995.940002],
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[1037.48999 ],
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[1094.      ],
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[1109.400024],
[1097.099976],
[1106.300049],
[1102.410034],
```

```
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```

```
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[1083.560059],
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[1079.      ],
[1079.02002 ],
[1064.890015],
[1063.030029],
```

```
       [1067.560059],
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       [1131.319946],
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       [1148.859985],
       [1143.650024],
       [1158.5     ],
       [1175.310059],
       [1174.849976],
       [1159.140015],
       [1143.599976],
       [1128.      ],
       [1121.339966],
       [1102.089966],
       [1120.      ]])
```

[41]:
```
inputs = sc.transform(inputs)
inputs.shape
```

[41]: (184, 1)

[42]:
```
x_test = []
for i in range(60,185):
    x_test.append(inputs[i-60:i,0])
```

[43]:
```
x_test = np.array(x_test)
x_test.shape
```

[43]: (125, 60)

[44]:
```
x_test = np.reshape(x_test, (x_test.shape[0],x_test.shape[1],1))
x_test.shape
```

[44]: (125, 60, 1)

[45]:
```
predicted_price = model.predict(x_test)
```

```
4/4              0s 38ms/step
```

[46]:
```
predicted_price = sc.inverse_transform(predicted_price)
predicted_price
```

```
[46]: array([[1024.4939 ],
       [1037.1158 ],
       [1053.3561 ],
       [1053.1577 ],
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       [1065.8434 ],
       [1055.375  ],
       [1066.7178 ],
       [1063.1041 ],
       [1089.0164 ],
       [1077.4818 ],
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       [1110.5964 ],
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       [1112.7155 ],
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       [1111.7554 ],
       [1080.8036 ],
       [1064.7714 ],
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       [1070.9989 ],
       [1038.7617 ],
       [1005.3588 ],
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       [1028.8955 ],
       [1026.8085 ],
       [1050.43   ],
       [1052.441  ],
       [1051.1024 ],
       [1065.4337 ],
       [1071.6688 ],
       [1067.0181 ],
       [1082.1649 ],
       [1091.71   ],
       [1074.0092 ],
       [1067.528  ],
       [1028.9415 ],
       [1055.8597 ],
       [1071.891  ],
       [1054.4053 ],
       [1077.4955 ],
       [1091.0834 ],
```

```
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[1088.2893 ],
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[1075.6495 ],
[1066.8552 ],
[1067.5449 ],
[1058.0524 ],
[1029.5642 ],
[1032.8052 ],
[1046.314  ],
[ 989.04767],
[1003.38055],
[1013.5712 ],
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[ 981.6454 ],
[1023.2588 ],
[ 999.3355 ],
[ 995.29736],
[1005.7834 ],
[1006.0806 ],
[1002.0341 ],
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[1043.164  ],
[1031.8541 ],
[1044.3013 ],
[1041.2863 ],
[1021.48145],
[1005.25946],
[1013.6051 ],
[1026.3016 ],
[1008.4108 ],
[ 995.941  ],
[1010.9883 ],
[1001.53406],
[ 998.4064 ],
[1025.5082 ],
[1027.8998 ],
[1024.2413 ],
[1049.1321 ],
[1051.7513 ],
[1055.5245 ],
[1048.2391 ],
[1041.8523 ],
```
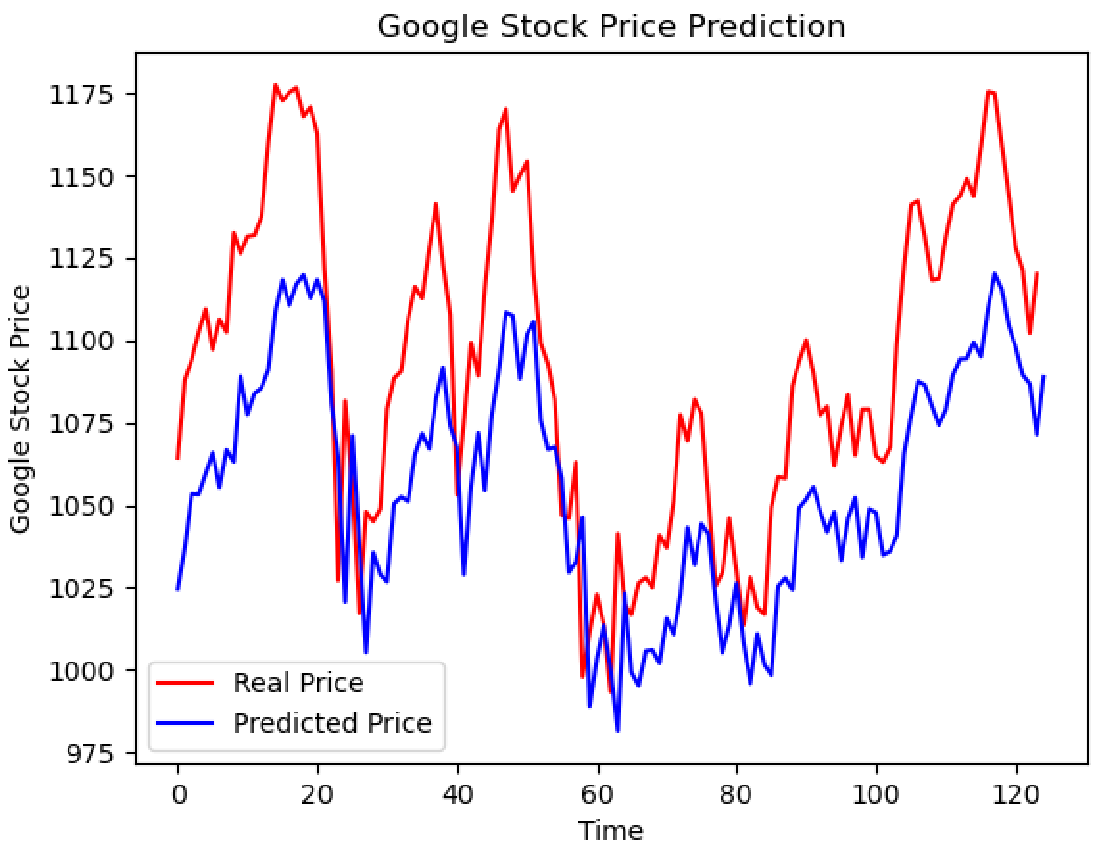

```
       [1047.9559 ],
       [1033.2684 ],
       [1045.8864 ],
       [1052.2167 ],
       [1034.217  ],
       [1048.8882 ],
       [1047.7574 ],
       [1034.8667 ],
       [1035.9879 ],
       [1040.8632 ],
       [1065.5171 ],
       [1077.2699 ],
       [1087.544  ],
       [1086.3931 ],
       [1079.9705 ],
       [1074.1661 ],
       [1078.9142 ],
       [1089.3608 ],
       [1094.2744 ],
       [1094.4103 ],
       [1099.3151 ],
       [1095.0126 ],
       [1109.3861 ],
       [1120.1135 ],
       [1115.3108 ],
       [1104.2882 ],
       [1097.8163 ],
       [1089.455  ],
       [1086.724  ],
       [1071.4109 ],
       [1088.8048 ]], dtype=float32)
```

[47]:
```
plt.plot(real_stock_price,color = 'red', label = 'Real Price')
plt.plot(predicted_price, color = 'blue', label = 'Predicted Price')
plt.title('Google Stock Price Prediction')
plt.xlabel('Time')
plt.ylabel('Google Stock Price')
plt.legend()
plt.show()
```


Google Stock Price Prediction
Google Stock Price
Time
1175
1150
1125
1100
1075
1050
1025
1000
975
0
20
40
60
80
100
120
Real Price
Predicted Price

[ ]: