```
In [1]:
          import pandas as pd
          import numpy as np
          import seaborn as sbn
          import matplotlib.pyplot as plt
In [2]:
          dataFrame = pd.read_excel("bisiklet_fiyatlari.xlsx")
In [3]:
          dataFrame
                    Fiyat BisikletOzellik1 BisikletOzellik2
Out[3]:
           0
               807.673876
                             1749.628226
                                           1749.590668
               959.227520
                             1748.007826
                                           1751.824206
               718.020033
                                           1747.977026
           2
                            1750.122967
           3
               945.668885
                            1749.916440
                                           1750.771646
                            1750.780519
               955.542968
                                           1750.592430
               833.920637
         995
                            1750.033229
                                           1749.427281
         996
              800.298076
                            1747.996913
                                           1750.035046
         997
               799.261737
                            1752.540381
                                           1747.983310
         998
               705.802257
                            1751.349290
                                           1747.484989
         999 1048.892414
                            1748.656426
                                           1752.539962
        1000 rows × 3 columns
In [4]:
         \# v = wx + b
         # y --> label yani fiyat
         y = dataFrame["Fiyat"].values #numpy array formatina çevir
         # x --> feature yani bisiklet özellikleri
         x = dataFrame[["BisikletOzellik1", "BisikletOzellik2"]].values
In [5]:
         from sklearn.model_selection import train_test_split
         #veri setini hem eğitim hem de test için ağırlıklı bi şekilde ikiye ayırmak için
         #test_size --> test için ayrılacak veri yüzdesi %33
         x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.33)
In [6]:
         x_train
Out[6]: array([[1750.482746, 1750.778662],
                [1747.277403, 1749.647984],
                [1750.512058, 1748.444974],
                [1748.268223, 1748.798416],
                [1753.324925, 1749.778418],
                [1748.195024, 1749.298745]])
         from sklearn.preprocessing import MinMaxScaler
```

```
#scaling --> tüm x değerlerini 0-1 arası değerlere ölçeklendirme
      scaler = MinMaxScaler()
      scaler.fit(x_train)
                       #ön hazırlık için uydur
      x_train = scaler.transform(x_train)
      x_test = scaler.transform(x_test)
In [8]:
      x train
Out[8]: array([[0.52320714, 0.60550034],
          [0.22536197, 0.49075659],
          [0.52593085, 0.36867243],
          [0.31743041, 0.40454052],
          [0.78730657, 0.50399333],
          [0.31062865, 0.45531503]])
In [9]:
      import tensorflow as tf
      from tensorflow.keras import models # model sinifi
      from tensorflow.keras import layers # katman sınıfı
In [10]:
      # Sinir Ağı Modeli Oluşturma
      model = models.Sequential()
      model.add(layers.Dense(4, activation="relu")) #1.qizli katman ve 4 nöron
      model.add(layers.Dense(4, activation="relu")) #2.gizli katman ve 4 nöron
      model.add(layers.Dense(4, activation="relu")) #3.gizli katman ve 4 nöron
      model.add(layers.Dense(1)) #çıkış katmanı
In [11]:
      # optimizasyon
      model.compile(optimizer="rmsprop", loss="mse")
In [12]:
      # eğitme
      model.fit(x train,y train, epochs=250)
      Epoch 1/250
      Epoch 2/250
      Epoch 3/250
      Epoch 4/250
      Epoch 5/250
      Epoch 6/250
      21/21 [============= ] - 0s 762us/step - loss: 784649.6250
      Epoch 7/250
      Epoch 8/250
      21/21 [================= ] - 0s 762us/step - loss: 783735.1250
      Epoch 9/250
      21/21 [================ ] - 0s 762us/step - loss: 783202.9375
      Epoch 10/250
      Epoch 11/250
      Epoch 12/250
```

```
Epoch 13/250
Epoch 14/250
Epoch 15/250
21/21 [=============== ] - 0s 762us/step - loss: 778657.0625
Epoch 16/250
Epoch 17/250
Epoch 18/250
Epoch 19/250
21/21 [=============== ] - 0s 762us/step - loss: 774019.1250
Epoch 20/250
Epoch 21/250
Epoch 22/250
Epoch 23/250
Epoch 24/250
Epoch 25/250
Epoch 26/250
Epoch 27/250
Epoch 28/250
Epoch 29/250
Epoch 30/250
Epoch 31/250
21/21 [=========== ] - 0s 953us/step - loss: 748878.0625
Epoch 32/250
Epoch 33/250
Epoch 34/250
Epoch 35/250
Epoch 36/250
Epoch 37/250
Epoch 38/250
Epoch 39/250
Epoch 40/250
21/21 [============= ] - 0s 952us/step - loss: 714635.8125
Epoch 41/250
21/21 [============= ] - 0s 953us/step - loss: 709820.3125
Epoch 42/250
21/21 [=========== ] - 0s 1ms/step - loss: 704771.5000
Epoch 43/250
Epoch 44/250
21/21 [============ ] - 0s 953us/step - loss: 693984.6250
Epoch 45/250
21/21 [============ ] - 0s 953us/step - loss: 688245.0000
Epoch 46/250
Epoch 47/250
Epoch 48/250
```

```
Epoch 49/250
21/21 [============= ] - 0s 952us/step - loss: 662701.5000
Epoch 50/250
Epoch 51/250
Epoch 52/250
Epoch 53/250
Epoch 54/250
Epoch 55/250
Epoch 56/250
Epoch 57/250
Epoch 58/250
Epoch 59/250
Epoch 60/250
Epoch 61/250
Epoch 62/250
Epoch 63/250
Epoch 64/250
21/21 [============= ] - 0s 953us/step - loss: 528612.9375
Epoch 65/250
Epoch 66/250
Epoch 67/250
Epoch 68/250
Epoch 69/250
Epoch 70/250
Epoch 71/250
Epoch 72/250
21/21 [============= ] - 0s 953us/step - loss: 432258.7188
Epoch 73/250
21/21 [============= ] - 0s 762us/step - loss: 419135.0000
Epoch 74/250
21/21 [============= ] - 0s 996us/step - loss: 405799.9375
Epoch 75/250
Epoch 76/250
21/21 [============= ] - 0s 952us/step - loss: 378537.0000
Epoch 77/250
Epoch 78/250
21/21 [=========== ] - 0s 1ms/step - loss: 350671.0312
Epoch 79/250
Epoch 80/250
21/21 [============ ] - 0s 953us/step - loss: 322371.8750
Epoch 81/250
Epoch 82/250
Epoch 83/250
Epoch 84/250
```

```
Epoch 85/250
Epoch 86/250
Epoch 87/250
Epoch 88/250
Epoch 89/250
Epoch 90/250
Epoch 91/250
21/21 [=============== ] - 0s 762us/step - loss: 165475.7188
Epoch 92/250
Epoch 93/250
Epoch 94/250
Epoch 95/250
Epoch 96/250
Epoch 97/250
Epoch 98/250
Epoch 99/250
21/21 [============== ] - 0s 953us/step - loss: 68880.8203
Epoch 100/250
21/21 [============== ] - 0s 1ms/step - loss: 59151.8047
Epoch 101/250
21/21 [============== ] - 0s 953us/step - loss: 50077.1797
Epoch 102/250
Epoch 103/250
Epoch 104/250
21/21 [============ ] - 0s 1ms/step - loss: 27954.5996
Epoch 105/250
Epoch 106/250
21/21 [============ ] - 0s 1ms/step - loss: 17886.4277
Epoch 107/250
Epoch 108/250
Epoch 109/250
Epoch 110/250
Epoch 111/250
Epoch 112/250
Epoch 113/250
Epoch 114/250
Epoch 115/250
Epoch 116/250
Epoch 117/250
Epoch 118/250
21/21 [============= ] - 0s 1ms/step - loss: 9114.1201
Epoch 119/250
Epoch 120/250
21/21 [============= ] - 0s 1ms/step - loss: 8942.1885
```

```
Epoch 121/250
21/21 [============= ] - 0s 953us/step - loss: 8868.8613
Epoch 122/250
Epoch 123/250
Epoch 124/250
Epoch 125/250
21/21 [============== ] - 0s 953us/step - loss: 8534.0039
Epoch 126/250
Epoch 127/250
21/21 [=========== - 0s 953us/step - loss: 8376.8213
Epoch 128/250
Epoch 129/250
Epoch 130/250
Epoch 131/250
Epoch 132/250
Epoch 133/250
Epoch 134/250
Epoch 135/250
Epoch 136/250
Epoch 137/250
Epoch 138/250
21/21 [=========== ] - 0s 1ms/step - loss: 7456.7329
Epoch 139/250
Epoch 140/250
21/21 [============ ] - 0s 952us/step - loss: 7300.2231
Epoch 141/250
Epoch 142/250
Epoch 143/250
Epoch 144/250
Epoch 145/250
Epoch 146/250
Epoch 147/250
Epoch 148/250
Epoch 149/250
Epoch 150/250
21/21 [============== ] - 0s 952us/step - loss: 6551.6084
Epoch 151/250
21/21 [=========== ] - 0s 1ms/step - loss: 6466.8618
Epoch 152/250
Epoch 153/250
Epoch 154/250
21/21 [============== ] - 0s 1ms/step - loss: 6223.8062
Epoch 155/250
21/21 [============== ] - 0s 1ms/step - loss: 6148.2681
Epoch 156/250
```

```
Epoch 157/250
Epoch 158/250
Epoch 159/250
21/21 [=========== - 0s 1ms/step - loss: 5863.0615
Epoch 160/250
Epoch 161/250
Epoch 162/250
Epoch 163/250
21/21 [=========== ] - 0s 1ms/step - loss: 5588.3140
Epoch 164/250
Epoch 165/250
Epoch 166/250
Epoch 167/250
Epoch 168/250
Epoch 169/250
Epoch 170/250
Epoch 171/250
Epoch 172/250
Epoch 173/250
Epoch 174/250
21/21 [=========== ] - 0s 1ms/step - loss: 4790.3838
Epoch 175/250
21/21 [=========== ] - 0s 952us/step - loss: 4718.2681
Epoch 176/250
21/21 [=========== ] - 0s 952us/step - loss: 4641.7847
Epoch 177/250
Epoch 178/250
Epoch 179/250
Epoch 180/250
Epoch 181/250
Epoch 182/250
Epoch 183/250
Epoch 184/250
Epoch 185/250
Epoch 186/250
Epoch 187/250
Epoch 188/250
Epoch 189/250
Epoch 190/250
21/21 [============= ] - 0s 1ms/step - loss: 3697.0867
Epoch 191/250
Epoch 192/250
```

```
Epoch 193/250
Epoch 194/250
21/21 [============= ] - 0s 953us/step - loss: 3435.9993
Epoch 195/250
Epoch 196/250
Epoch 197/250
Epoch 198/250
21/21 [==============] - 0s 1ms/step - loss: 3186.6326
Epoch 199/250
Epoch 200/250
Epoch 201/250
Epoch 202/250
Epoch 203/250
Epoch 204/250
Epoch 205/250
Epoch 206/250
Epoch 207/250
Epoch 208/250
Epoch 209/250
Epoch 210/250
21/21 [=========== ] - 0s 953us/step - loss: 2462.7883
Epoch 211/250
Epoch 212/250
Epoch 213/250
Epoch 214/250
Epoch 215/250
Epoch 216/250
Epoch 217/250
Epoch 218/250
Epoch 219/250
Epoch 220/250
Epoch 221/250
Epoch 222/250
Epoch 223/250
Epoch 224/250
21/21 [============= ] - 0s 1ms/step - loss: 1677.0576
Epoch 225/250
21/21 [============== ] - 0s 1ms/step - loss: 1621.5319
Epoch 226/250
21/21 [============= ] - 0s 1ms/step - loss: 1567.0109
Epoch 227/250
```

Epoch 228/250

```
Epoch 229/250
   Epoch 230/250
   Epoch 231/250
   Epoch 232/250
   Epoch 233/250
   Epoch 234/250
   Epoch 235/250
   21/21 [=========== ] - 0s 1ms/step - loss: 1135.7925
   Epoch 236/250
   Epoch 237/250
   Epoch 238/250
   Epoch 239/250
   Epoch 240/250
   21/21 [=========== - 0s 1ms/step - loss: 916.3654
   Epoch 241/250
   21/21 [============ - 0s 953us/step - loss: 878.5037
   Epoch 242/250
   Epoch 243/250
   21/21 [============ - 0s 953us/step - loss: 801.9258
   Epoch 244/250
   Epoch 245/250
   Epoch 246/250
   Epoch 247/250
   Epoch 248/250
   21/21 [============ ] - 0s 952us/step - loss: 621.3063
   Epoch 249/250
   21/21 [============ ] - 0s 953us/step - loss: 590.1779
   Epoch 250/250
   21/21 [=========== ] - 0s 1ms/step - loss: 564.5442
Out[12]: <tensorflow.python.keras.callbacks.History at 0x21939237b50>
In [13]:
    # Loss değerlerinin minimize olma eğrisi
    loss = model.history.history["loss"]
    axis = range(0,len(loss))
    plt.plot(axis,loss)
```

Out[13]: [<matplotlib.lines.Line2D at 0x2193a861e80>]

```
800000 -

700000 -

500000 -

400000 -

200000 -

100000 -

0 -

0 50 100 150 200 250
```

```
In [14]:
          # Loss kayıplarının değerlendirilmesi
          # train ve test kayıpları ne kadar az olursa o kadar iyidir
          # train ve test kayıplarının birbirine yakın değerler olması sağlıklıdır
          trainLoss = model.evaluate(x_train,y_train,verbose=0)
          testLoss = model.evaluate(x test,y test,verbose=0)
In [15]:
          trainLoss
Out[15]: 544.71435546875
In [16]:
          testLoss
Out[16]: 569.54345703125
In [17]:
          # Tahmin denemeleri
          tahminler = model.predict(x_test)
          # y --> fiyat tahminlerini numpy array şeklinde verir
          tahminler.shape
Out[17]: (330, 1)
In [18]:
          tahminler = pd.Series(tahminler.reshape(330,))
          tahminler
                  604.519287
Out[18]: 0
                  958.786560
                 791.092102
         3
                 1028.104614
         4
                 947.453674
         325
                1192.929688
                 899.815979
         326
                 765.805908
         327
         328
                 954.215393
         329
                 792.958984
         Length: 330, dtype: float32
In [19]:
          # Tahminlerin gerçek değerlerle karşılaştırılması
          compareFrame = pd.DataFrame(y_test,columns=["Gerçek Fiyat"])
```

```
compareFrame = pd.concat([compareFrame,tahminler],axis=1)
compareFrame.columns = ["Gerçek Fiyat","Tahmin"]
```

### In [20]:

compareFrame

#### Out[20]:

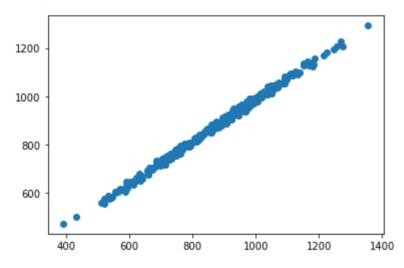
	Gerçek Fiyat	Tahmin
0	566.556564	604.519287
1	977.111437	958.786560
2	786.552347	791.092102
3	1042.940184	1028.104614
4	965.387674	947.453674
•••		
325	1245.401103	1192.929688
326	897.021611	899.815979
327	744.107388	765.805908
328	957.475775	954.215393
329	789.208125	792.958984

330 rows × 2 columns

#### In [21]:

plt.scatter(y\_test,tahminler)

# Out[21]: <matplotlib.collections.PathCollection at 0x2193a9e46a0>



## In [22]:

model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 4)	12
dense_1 (Dense)	(None, 4)	20
dense_2 (Dense)	(None, 4)	20
dense_3 (Dense)	(None, 1)	5

Total params: 57
Trainable params: 57
Non-trainable params: 0

```
In [23]:
          # Hata oranı kabul edilebilir mi?
          from sklearn.metrics import mean_absolute_error
          mean_absolute_error(compareFrame["Gerçek Fiyat"],compareFrame["Tahmin"])
Out[23]: 18.99912551246567
In [24]:
          dataFrame["Fiyat"].mean()
Out[24]: 872.6778007425
In [25]:
          # ortalama 872 liralık fiyatlardan ortalama 6.94 tl sapabilir
In [26]:
          # modeli kaydetme
          model.save("bisiklet_modeli.h5")
          # modeli alma
          # from tensorflow.keras.models import load model
          # my_model = load_model("bisiklet_modeli.h5")
 In [ ]:
```