TensorFlow

In [1]:

import pandas as pd

In [2]:

dataFrame = pd.read_excel("bisiklet_fiyatlari.xlsx")

In [3]:

dataFrame

Out[3]:

	Fiyat	BisikletOzellik1	BisikletOzellik2
0	807.673876	1749.628226	1749.590668
1	959.227520	1748.007826	1751.824206
2	718.020033	1750.122967	1747.977026
3	945.668885	1749.916440	1750.771646
4	955.542968	1750.780519	1750.592430
995	833.920637	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]:

dataFrame.head()

Out[4]:

	Fiyat	BisikletOzellik1	BisikletOzellik2
0	807.673876	1749.628226	1749.590668
1	959.227520	1748.007826	1751.824206
2	718.020033	1750.122967	1747.977026
3	945.668885	1749.916440	1750.771646
4	955.542968	1750.780519	1750.592430

In [5]:

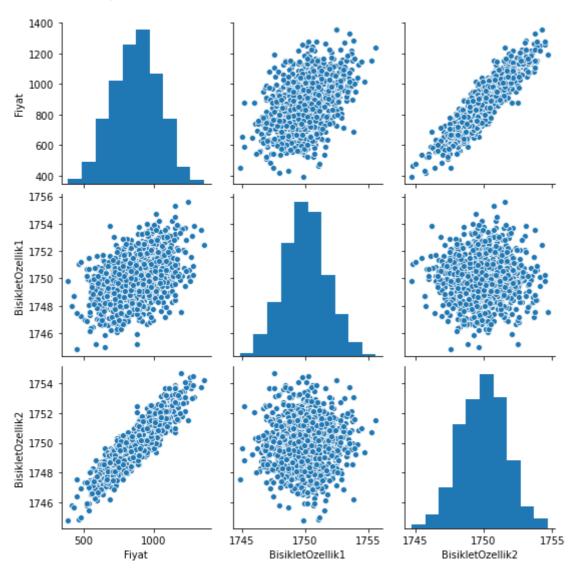
```
import seaborn as sbn
import matplotlib.pyplot as plt
```

In [6]:

sbn.pairplot(dataFrame)

Out[6]:

<seaborn.axisgrid.PairGrid at 0x24279096310>



Data Train/Test

In [7]:

from sklearn.model_selection import train_test_split

In [8]:

#train_test_spilte

In [9]:

dataFrame

Out[9]:

	Fiyat	BisikletOzellik1	BisikletOzellik2
0	807.673876	1749.628226	1749.590668
1	959.227520	1748.007826	1751.824206
2	718.020033	1750.122967	1747.977026
3	945.668885	1749.916440	1750.771646
4	955.542968	1750.780519	1750.592430
995	833.920637	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 [10]:

```
# y = wx + b
# y = label
# x = feature (özellik)

y = dataFrame["Fiyat"].values #numpy dizisine çevirir

x = dataFrame[["BisikletOzellik1", "BisikletOzellik2"]].values

x_train , x_test , y_train , y_test = train_test_split(x,y,test_size=0.33,random_state=15)
```

In [11]:

```
x_train.shape # özellik olduğu için iki sütun var
```

Out[11]:

(670, 2)

In [12]:

```
x_test.shape
```

Out[12]:

(330, 2)

```
In [13]:
y_train.shape #fiyat olduğu için tek sütun var
Out[13]:
(670,)
In [14]:
y_test.shape
Out[14]:
(330,)
scaling
In [15]:
from sklearn.preprocessing import MinMaxScaler
In [16]:
scaler = MinMaxScaler()
In [17]:
scaler.fit(x_train)
Out[17]:
MinMaxScaler()
In [18]:
x_train = scaler.transform(x_train)
x_test = scaler.transform(x_test)
In [19]:
x_train #veriler normalize edildi (0,1) aralığında
Out[19]:
array([[0.3177906 , 0.64341466],
       [0.61991638, 0.89583174],
       [0.53950097, 0.0980286],
       [0.2352117, 0.52644765],
       [0.7576794, 0.19157421],
       [0.4292982 , 0.16530301]])
In [20]:
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

In [21]:

```
model = Sequential()
model.add(Dense(4,activation = "relu"))
model.add(Dense(4,activation = "relu"))
model.add(Dense(4,activation = "relu"))
model.add(Dense(1))
model.compile(optimizer = "rmsprop", loss = "mse")
```

In [22]:

model.fit(x_train,y_train,epochs=250)

Epoch 1/250 21/21 [====================================
Epoch 2/250
21/21 [====================================
Epoch 3/250
21/21 [====================================
Epoch 4/250
21/21 [====================================
Epoch 5/250
21/21 [====================================
Epoch 6/250
21/21 [====================================
21/21 [====================================
Epoch 8/250
21/21 [====================================
Epoch 9/250
21/21 [====================================
Epoch 10/250
21/21 [====================================
21/21 [====================================
Epoch 12/250
21/21 [====================================
Epoch 13/250
21/21 [====================================
Epoch 14/250
21/21 [====================================
Epoch 15/250 21/21 [====================================
Epoch 16/250
21/21 [====================================
Epoch 17/250
21/21 [====================================
Epoch 18/250
21/21 [====================================
Epoch 19/250 21/21 [====================================
Epoch 20/250
21/21 [====================================
Epoch 21/250
21/21 [====================================
Epoch 22/250
21/21 [====================================
Epoch 23/250 21/21 [====================================
s/step - loss: 778131.4176
Epoch 24/250
21/21 [====================================
Epoch 25/250
21/21 [====================================
Epoch 26/250 21/21 [====================================
Epoch 27/250
21/21 [====================================
Epoch 28/250
21/21 [====================================
Epoch 29/250
21/21 [====================================
Epoch 30/250 21/21 [====================================
21/21 [

 	2. (2.2.)						
	31/250 [=======]	_	05	2ms/sten	_	loss:	763409.6733
	32/250		03	23, 3 сер		1055.	703403.0733
	[======]	-	0s	3ms/step	-	loss:	737740.2386
	33/250		_			-	
	[=======] 34/250	-	0s	4ms/step	-	loss:	755912.9205
•	[=========]	_	05	3ms/sten	_	loss:	734217.6449
	35/250			ээ, э сер			70.127.00.17
	[======]	-	0s	3ms/step	-	loss:	752172.5256
	36/250		^	2 / 1		,	727507 4222
	[=======] 37/250	-	05	2ms/step	-	TOSS:	/3/59/.4233
	[========]	_	0s	4ms/step	-	loss:	727210.4915
Epoch	38/250						
	[========]	-	0s	4ms/step	-	loss:	739098.2216
	39/250 [=======]		۵۶	3mc/stan	_	1000	71/168 207/
	40/250	_	03	Jiii3/3 Cep		1033.	714100.2074
	[========]	-	0s	4ms/step	-	loss:	715326.5597
	41/250					_	
	[========] 42/250	-	0s	4ms/step	-	loss:	685038.0142
•	42/250 [========]	_	05	4ms/sten	_	loss:	686303.6903
	43/250			э, э сер			
	[======]	-	0s	3ms/step	-	loss:	681767.4460
	44/250 [========]		0.5	2ms/s+on		1000	CEC730 07C7
	45/250	-	62	3ms/scep	-	1055:	050/30.0/0/
	[========]	_	0s	4ms/step	-	loss:	656867.6278
•	46/250						
	[=========]	-	0s	4ms/step	-	loss:	651135.0739
	47/250 [========]	_	05	2ms/sten	_	loss:	637561.9347
	48/250			, 5 ccp			00700=11017
	[=======]	-	0s	3ms/step	-	loss:	626056.9489
•	49/250 [========]		0.5	Emc/ston		10001	630690 9466
	50/250	-	62	oms/scep	-	1055.	020009.0400
	[========]	-	0s	3ms/step	-	loss:	619667.0511
•	51/250						
	[=========]	-	0s	3ms/step	-	loss:	580766.2386
	52/250 [=======]	_	0s	4ms/step	_	loss:	589530.3722
	53/250			, с с с р			
	[=======]	-	0s	4ms/step	-	loss:	577337.9034
•	54/250 [=======]		0.5	2mc/c+on		1000	E60E92 2602
	55/250	_	62	oms/scep	-	1055.	300362.3093
•	[========]	-	0s	6ms/step	-	loss:	536909.4290
•	56/250					_	
	[=======] 57/250	-	0s	4ms/step	-	loss:	525057.8920
	[========]	_	0s	4ms/step	_	loss:	510672.3054
Epoch	58/250						
	[========]	-	0s	2ms/step	-	loss:	487080.5369
•	59/250 [=======]	_	۵۰	Ams/stan	_	1000	469173 5 <u>8</u> 95
	60/250	-	US		_	1033.	-UJI/J.J09J
21/21	[======]	-	0s	4ms/step	-	loss:	459087.0199
Epoch	61/250						

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	[]	-	0s	4ms/step -	loss:	440304.5355
•	62/250 [=======]		0.5	2mc/ston	10551	410070 143E
	63/250	-	62	oms/step -	1055.	4100/0.1433
•	[========]	-	0s	4ms/step -	loss:	402408.5099
	64/250				_	
	[========] 65/250	-	0s	5ms/step -	loss:	386618.5000
	[========]	_	0s	4ms/step -	loss:	367018.2216
Epoch	66/250			-		
	[=========]	-	0s	3ms/step -	loss:	347870.5639
	67/250 [=======]	_	05	4ms/sten -	loss:	332805.2230
	68/250		0.5	э, э сер	1033.	33200312230
	[======]	-	0s	3ms/step -	loss:	304424.2216:
	loss: 304472.89 69/250					
•	[========]	_	0s	3ms/step -	loss:	287617.9545
Epoch	70/250			•		
	[======================================	-	0s	2ms/step -	loss:	275493.5895
	71/250	_	05	4ms/sten -	loss:	246376.1328
	72/250					
	[=======]	-	0s	4ms/step -	loss:	228834.5249
	73/250 [========]	_	۵c	3ms/sten -	1055.	213091 6776
	74/250		03	эшэ/ эсср	1033.	213031.0770
	[=======]	-	0s	3ms/step -	loss:	188662.4972
•	75/250 [========]	_	۵c	3ms/stan -	1000	173333 0568
	76/250		03	Jiiis/ scep -	1033.	175555.0508
	[======]	-	0s	2ms/step -	loss:	153439.9943
•	77/250 [=======]		۵۶	Ams/ston -	1000	1/0902 1059
	78/250	_	03	41113/3CEP -	1033.	140003.1030
	[======]	-	0s	4ms/step -	loss:	121874.8271
•	79/250 [=======]		0.5	2mc/ston	10551	100655 7522
	80/250	-	62	oms/step -	1055.	100055.7552
	[======]	-	0s	4ms/step -	loss:	88469.9151
•	81/250		0.5	Fmc/ston	10551	COOF1 1202
	[=====================================	-	05	sms/step -	1055:	69051.1303
•	[========]	-	0s	2ms/step -	loss:	56833.2607
•	83/250		0 -	A / - +	1	47120 2460
	[=====================================	-	05	4ms/step -	1055:	4/120.2468
•	[========]	-	0s	3ms/step -	loss:	35316.5045
	85/250		_	2 ()	-	04644 4764
	[=======] 86/250	-	0s	3ms/step -	loss:	24641.4764
	[=========]	-	0s	4ms/step -	loss:	17916.6188
•	87/250				_	
	[========] 88/250	-	0s	6ms/step -	loss:	11685.1748
•	[=========]	_	0s	5ms/step -	loss:	8654.8494
Epoch	89/250			-		
	[========]	-	0s	2ms/step -	loss:	5880.5110
•	90/250 [=======]	_	0s	4ms/step -	loss:	5525.4478
	91/250		-	r		

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	[======]	-	0s	4ms/step	-	loss:	6221.9880
•	92/250		_	.		_	
	[=========]	-	0s	6ms/step	-	loss:	5804.1733
	93/250 [=======]		۵c	3mc/cton	_	1000	5631 1640
	94/250		03	Jiii3/3 CEP		1033.	3031.1040
	[========]	_	0s	3ms/step	_	loss:	5645.3491
	95/250			•			
	[======]	-	0s	5ms/step	-	loss:	5121.3628
	96/250					_	
	[======================================	-	0s	5ms/step	-	loss:	5385.3230
	97/250 [=======]	_	۵c	3ms/stan	_	1000	5051 3769
	98/250		03	эшэ/ эсср		1033.	3031.3703
	[========]	_	0s	5ms/step	-	loss:	5079.0269
	99/250			·			
	[=======]	-	0s	2ms/step	-	loss:	4981.3822
•	100/250		0 -	C / - +		7	E1E1 7000
	[=======] 101/250	-	05	6ms/step	-	TOSS:	5151./828
	[=========]	_	0s	4ms/step	_	loss:	4666,2907
	102/250			, с с с р			
21/21	[======]	-	0s	4ms/step	-	loss:	4664.8977
	103/250			-		-	
	[======================================	-	0s	3ms/step	-	loss:	4657.9019
	104/250	_	۵ς	3ms/sten	_	1055.	<i>4</i> 711 9083
	105/250		03	эшэ, эсср		1033.	4711.5005
	[=======]	-	0s	4ms/step	-	loss:	4381.9669
	106/250						
	[========]	-	0s	4ms/step	-	loss:	4314.3991
	107/250 [======]		۵c	3mc/stan	_	1000.	1127 1906
	108/250		03	Jiii3/3 CEP		1033.	4127.4700
•	[=======]	-	0s	3ms/step	-	loss:	4133.1018
	109/250						
	[========]	-	0s	4ms/step	-	loss:	3846.6632
•	110/250 [=======]		0.0	2mc/cton		1000	2004 0240
	111/250	_	03	Jiiis/ s cep	_	1055.	3004.3340
	[=========]	_	0s	3ms/step	_	loss:	3673.9326
	112/250			·			
	[=======]	-	0s	4ms/step	-	loss:	3804.4983
	113/250 [=======]		0.5	Emc/c+on		1000	2526 2050
	114/250	_	62	ollis/step	-	1055.	3330.2036
	[=========]	_	0s	4ms/step	_	loss:	3566.3787
Epoch	115/250						
	[======]	-	0s	3ms/step	-	loss:	3349.0828
	116/250 [=======]		0.5	2ms/ston		1000	2221 7217
	117/250	-	62	siis/s cep	-	1055:	3331./21/
	[=========]	_	0s	5ms/step	_	loss:	3218.7800
Epoch	118/250						
	[======]	-	0s	4ms/step	-	loss:	3594.3527
	119/250 [=======]		0-	1mc/c+a=		1000	2017 0252
	120/250	-	25	41115/5cep	-	1022;	אכאס. / דשכ
•	[=========]	_	0s	3ms/step	-	loss:	2696.6337
Epoch	121/250			·			
21/21	[======]	-	0s	3ms/step	-	loss:	2864.1667

г	122/250						
	122/250 [=======]	_	05	4ms/sten	_	loss:	2955.0357
	123/250		03	-11137 3 сср		1033.	2000.0007
	[========]	-	0s	3ms/step	-	loss:	2750.9377
Epoch	124/250			•			
	[======]	-	0s	3ms/step	-	loss:	2598.9972
•	125/250			_		_	
	[========]	-	0s	4ms/step	-	loss:	2503.6571
	126/250 [=======]		0.5	1ms /s+on		1000	2506 9000
	127/250	-	62	4ms/scep	_	1055:	2506.8009
	[=========]	_	05	3ms/step	_	loss:	2466.3780
	128/250			ээ, э сер			
21/21	[======]	-	0s	4ms/step	-	loss:	2347.1685
	129/250						
	[=======]	-	0s	4ms/step	-	loss:	2356.2008
	130/250		0 -	A		7	2402 7445
	[=======] 131/250	-	ØS.	4ms/step	-	loss:	2183./115
	[=========]	_	۵s	4ms/sten	_	1055.	2187 7007
	132/250		03	-13, 3 сер		1033.	2107.7007
•	[=======]	-	0s	3ms/step	-	loss:	2005.7729
•	133/250						
	[=======]	-	0s	4ms/step	-	loss:	1895.2101
•	134/250		^	4 / 1		-	4045 7000
	[========] 135/250	-	0s	4ms/step	-	loss:	1845.7802
	[=========]	_	۵s	Ams/sten	_	1055.	1996 3649
	136/250		03	-1113/ 3 сср		1033.	1000.0040
	[========]	_	0s	4ms/step	-	loss:	1749.8695
	137/250			·			
	[======]	-	0s	4ms/step	-	loss:	1838.4294
	138/250		_	2 / 1		-	4676 7406
	[=======] 139/250	-	ØS.	3ms/step	-	loss:	16/6./126
	[=========]	_	95	4ms/sten	_	loss:	1627.3364
	140/250		03	-13, 3 сер		1033.	1027.3304
	[=======]	-	0s	4ms/step	-	loss:	1607.3791
•	141/250						
	[=======]	-	0s	5ms/step	-	loss:	1475.3260
•	142/250		0 -	2		7	1400 0003
	[========] 143/250	-	05	3ms/step	-	TOSS:	1400.9883
	[=========]	_	95	4ms/sten	_	loss:	1478.1144
	144/250		0.5	э, э сер		1033.	11,0,111
21/21	[======]	-	0s	4ms/step	-	loss:	1219.7575
	145/250						
	[=======]	-	0s	3ms/step	-	loss:	1280.4427
•	146/250		0.5	2ms/ston		1000	1141 0506
	[========] 147/250	-	62	ziiis/step	_	1055:	1141.8586
•	[========]	_	0s	2ms/step	_	loss:	1120.4500
	148/250			-,			
	[======]	-	0s	2ms/step	-	loss:	1082.7016
	149/250		_			_	
	[======================================	-	0s	4ms/step	-	loss:	957.6769
•	150/250 [=======]	_	۵۰	3mc/c+0n	_	1000	963 5222
	151/250	_	05	عد رداارد (داارد	_	TO22.	703.3232
•	[=========]	_	0s	4ms/step	_	loss:	995.1195
	152/250			. г			

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	[======]	-	0s	3ms/step	loss:	858.3215
•	153/250		_	_ , .		
	[=====================================	-	0s	3ms/step	· loss:	814.5660
•	[==========]	_	۵s	3ms/sten .	. loss:	780 9309
	155/250		03	311137 3 CCP	1033.	700.5505
	[=======]	-	0s	4ms/step	loss:	645.1057
	156/250					
	[=======]	-	0s	3ms/step	· loss:	668.1909
	157/250 [========]	_	۵c	Sms/stan .	. 1055.	669 7976
	158/250		03	эшэ/ эсср	1033.	005.7570
	[=======]	-	0s	3ms/step	loss:	628.0273
	159/250				_	
	[========]	-	0s	4ms/step	· loss:	554.0577
•	160/250 [========]	_	۵c	/ms/stan .	. 1055.	521 6756
	161/250		03	-1 1113/300p	1033.	321.0730
•	[=======]	-	0s	4ms/step	loss:	483.8462
	162/250				_	
	[========]	-	0s	4ms/step	· loss:	458.6354
	163/250 [========]	_	۵s	2ms/sten .	. loss:	470 5127
	164/250		03	211137 3 CCP	1033.	470.5127
	[======]	-	0s	5ms/step	loss:	411.3132
	165/250				_	
	[========] 166/250	-	0s	5ms/step	· loss:	341.9629
	[=========]	_	95	5ms/sten	· loss:	366.0056
	167/250		0.5	33, 3 ccp	1033.	300.0030
	[======]	-	0s	4ms/step	· loss:	319.3723
	168/250		_	-		
	[========] 169/250	-	0s	3ms/step	· loss:	314.2778
	[========]	_	0s	4ms/step	· loss:	305.7127
Epoch	170/250			•		
	[======]	-	0s	4ms/step	loss:	277.5866
•	171/250		0-	2	1	255 0401
	[=========] 172/250	-	05	zms/step -	- 1055:	255.9401
•	[=========]	_	0s	4ms/step	loss:	249.5037
	173/250					
	[=======]	-	0s	2ms/step	· loss:	248.0198
	174/250 [========]		0.5	1ms/ston	1000	200 4202
	175/250	_	62	41113/3tep	. 1022.	200.4303
	[======]	-	0s	3ms/step	loss:	188.7190
	176/250					
	[========]	-	0s	3ms/step	· loss:	167.1973
	177/250 [========]	_	95	3ms/sten	. loss:	173 6278
	178/250		03	311137 3 CCP	1033.	175.0270
21/21	[======]	-	0s	4ms/step	loss:	154.0115
•	179/250		_	-		
	[========] 180/250	-	Øs	3ms/step ⋅	· loss:	136.3608
•	[=========]	_	0s	3ms/step	· loss:	134.4743
Epoch	181/250			·		
	[======]	-	0s	5ms/step	loss:	125.6560
•	182/250		0-	2mc/s+s=	1	111 2014
71/21	[=======]	-	ØS	oms/step ·	· 1022;	111.3614

	183/250 [========]	_	0s	2ms/step -	loss:	113.4453
Epoch	184/250 [========]			-		
	185/250	-	05	/ms/scep -	1055:	101.0863
	[=========] 186/250	-	0s	6ms/step -	loss:	98.4270
•	[========]	-	0s	2ms/step -	loss:	96.4660
•	187/250 [=======]		۵c	3ms/stan -	1000	96 5721
Epoch	188/250					
	[========] 189/250	-	0s	4ms/step -	loss:	88.9642
21/21	[======]	-	0s	5ms/step -	loss:	83.7325: 0s -
loss:	80.47 190/250					
•	[=========]	_	95	4ms/sten -	loss:	85.1399
	191/250		0.5	3, 3 ccp	1033.	03.1333
21/21	[======]	-	0s	5ms/step -	loss:	80.5956
•	192/250 [========]		۵۶	2ms/ston -	1000	92 0710
	193/250	_	05	oms/step -	1055.	03.0/10
	[======]	-	0s	4ms/step -	loss:	83.4452
•	194/250		0-	A	1	01 0202
	[=====================================	-	05	4ms/step -	1055:	81.9292
	[=========]	-	0s	5ms/step -	loss:	76.0517
•	196/250		0 -	2	1	02 0057
	[=====================================	-	05	Zms/step -	1055:	83.985/
	[========]	-	0s	3ms/step -	loss:	71.5216
	198/250		_		,	
	[=====================================	-	0s	4ms/step -	loss:	//.8/4/IA: 0s
	199/250					
	[]	-	0s	6ms/step -	loss:	75.9725
•	200/250		۵c	2ms/stan -	1000	78 8607
	201/250		03	21113/3 CCP	1033.	70.0007
	[=======]	-	0s	4ms/step -	loss:	78.5864
•	202/250	_	۵ς	3ms/sten -	loss	79 2111
	203/250		03	Jiii3/ 3 CCP	1033.	73.2111
	[======]	-	0s	3ms/step -	loss:	76.4006
•	204/250 [==========]	_	۵c	/ms/stan -	1000	7/1 6/112
	205/250		03	41113/3CEP -	1033.	74.0412
	[======]	-	0s	5ms/step -	loss:	74.9816
•	206/250		۵۶	2ms/ston -	1000	70 7597
	207/250	_	03	Jiii3/3 Cep -	1033.	79.7387
21/21	[======]	-	0s	3ms/step -	loss:	80.1214
•	208/250		0.5	Ams/stan	10001	72 9001
	209/250	-	05	41113/3CEP -	1055.	72.0991
21/21	[======]	-	0s	3ms/step -	loss:	76.3119
•	210/250		00	2mc/c+00	10551	77 0190
	211/250	-	02	יייכיייכיייכיייכיייכיייכיייכיייכיייכיי	TO22.	//.0103
21/21	[=======]	-	0s	4ms/step -	loss:	73.3791
Epoch	212/250					

```
21/21 [============= ] - 0s 4ms/step - loss: 77.3728
Epoch 213/250
Epoch 214/250
Epoch 215/250
Epoch 216/250
Epoch 217/250
ep - loss: 73.5645
Epoch 218/250
21/21 [============== ] - 0s 4ms/step - loss: 76.9222
Epoch 219/250
Epoch 220/250
Epoch 221/250
21/21 [============== ] - 0s 4ms/step - loss: 80.1434
Epoch 222/250
21/21 [============== ] - 0s 4ms/step - loss: 75.0157
Epoch 223/250
21/21 [============== ] - 0s 5ms/step - loss: 79.8935
Epoch 224/250
Epoch 225/250
Epoch 226/250
21/21 [============== ] - 0s 4ms/step - loss: 72.1854
Epoch 227/250
21/21 [============== ] - 0s 4ms/step - loss: 80.8372
Epoch 228/250
Epoch 229/250
Epoch 230/250
21/21 [============== ] - 0s 4ms/step - loss: 74.8372
Epoch 231/250
Epoch 232/250
Epoch 233/250
Epoch 234/250
Epoch 235/250
21/21 [================== ] - 0s 3ms/step - loss: 74.3672
Epoch 236/250
21/21 [================== ] - 0s 4ms/step - loss: 73.9107
Epoch 237/250
Epoch 238/250
21/21 [================== ] - 0s 6ms/step - loss: 74.8602
Epoch 239/250
21/21 [================== ] - 0s 4ms/step - loss: 75.3521
Epoch 240/250
Epoch 241/250
Epoch 242/250
```

```
21/21 [============== ] - 0s 4ms/step - loss: 75.4915
Epoch 243/250
Epoch 244/250
Epoch 245/250
21/21 [=========== ] - 0s 4ms/step - loss: 78.4355
Epoch 246/250
Epoch 247/250
21/21 [============ ] - 0s 3ms/step - loss: 77.0681
Epoch 248/250
Epoch 249/250
Epoch 250/250
```

Out[22]:

<tensorflow.python.keras.callbacks.History at 0x2424c85ae50>

In [23]:

```
loss = model.history.history["loss"]
```

In [24]:

loss

Out[24]:

[795862.5625,

795740.1875, 795583.4375, 795376.9375, 795132.5625, 794860.125, 794551.8125, 794205.0625, 793814.375, 793377.9375, 792887.0, 792340.1875, 791721.9375, 791005.5, 790192.875, 789273.5, 788234.875, 787060.4375, 785741.0, 784276.375, 782638.6875, 780827.6875, 778827.4375, 776623.625, 774201.5, 771556.875, 768673.4375, 765530.5625, 762127.0625, 758431.6875, 754429.125, 750097.125, 745465.1875, 740478.0, 735163.0, 729453.6875, 723347.6875, 716878.25, 709959.125, 702629.125, 694840.4375, 686630.375, 677991.625, 668797.4375, 659152.375, 649026.3125, 638414.1875, 627314.375, 615700.0625, 603582.5625, 590844.6875, 577681.125, 564020.0625, 549802.0625, 535025.125, 519773.46875, 504072.25, 487855.625, 471115.09375,

454015.375, 436486.875, 418533.21875, 400226.59375, 381583.90625, 362647.4375, 343452.15625, 324036.75, 304346.1875, 284617.09375, 264996.625, 245224.28125, 225556.28125, 206126.296875 186897.546875, 168042.09375, 149643.609375, 131871.125, 114678.640625, 98150.6796875, 82753.53125, 68252.3515625 54960.69140625, 43190.9296875, 32767.58203125, 23888.662109375, 16818.623046875, 11463.318359375, 8108.154296875, 6397.04541015625, 5921.81201171875, 5820.64013671875, 5710.6474609375, 5586.63623046875, 5482.8076171875, 5367.70068359375, 5249.65185546875, 5147.173828125, 5034.14501953125, 4935.5947265625, 4835.62841796875, 4738.6904296875, 4635.62646484375, 4537.720703125, 4430.00537109375, 4332.2763671875, 4239.6337890625, 4151.84619140625 4056.906005859375, 3962.6787109375, 3882.0537109375 3799.750732421875, 3712.397705078125, 3628.205322265625, 3522.280517578125, 3441.428466796875, 3340.47509765625, 3262.35791015625, 3176.142578125, 3084.99560546875, 3006.468017578125,

2919.03564453125, 2841.214111328125, 2750.802490234375, 2672.5869140625, 2598.07861328125, 2530.238525390625, 2456.05517578125, 2376.522705078125, 2298.59765625, 2207.92626953125, 2131.141845703125 2050.260986328125, 1976.597412109375, 1912.1649169921875 1841.1927490234375, 1774.2454833984375, 1712.4261474609375, 1638.6822509765625, 1579.6734619140625, 1523.045654296875, 1452.8563232421875, 1389.1002197265625, 1328.797607421875, 1273.75927734375, 1225.4149169921875, 1172.02392578125, 1123.4349365234375, 1071.8060302734375, 1020.8250732421875, 973.4327392578125, 919.22314453125, 872.1087646484375, 830.3506469726562, 785.3709716796875, 741.678955078125, 699.5709838867188, 657.1301879882812, 618.92578125, 578.6229248046875, 538.4347534179688, 501.0659484863281, 467.9807434082031, 440.1975402832031, 409.8994445800781, 384.3705749511719 357.95880126953125, 332.7665710449219, 311.2568664550781, 290.3519287109375, 269.95465087890625, 248.7427215576172, 231.61692810058594, 216.87750244140625, 198.5242462158203, 184.69622802734375, 169.53176879882812, 161.62338256835938, 149.84336853027344, 138.63807678222656, 127.59834289550781, 120.83782958984375,

111.97826385498047, 105.7383041381836, 101.61418914794922, 97.93712615966797, 94.3680648803711, 91.75080108642578, 88.50908660888672, 86.7975082397461, 84.0705337524414, 82.88314819335938, 81.6921615600586, 79.95585632324219, 78.56197357177734, 78.85204315185547, 76.98045349121094, 77.49833679199219, 76.1550521850586, 75.3633041381836, 75.69584655761719 77.57504272460938, 75.24401092529297, 75.15885925292969 75.00592041015625, 74.35660552978516, 75.31068420410156, 75.18805694580078, 74.88079071044922, 74.0020523071289, 75.54693603515625 75.21373748779297, 74.87848663330078, 75.41053771972656, 74.93064880371094, 76.36326599121094, 75.72454833984375, 75.43600463867188, 73.82840728759766, 75.70954132080078, 74.5927505493164, 75.19747924804688 75.14496612548828, 75.32838439941406, 74.71129608154297, 73.81000518798828, 75.14491271972656, 74.18317413330078, 74.99443054199219, 76.0055160522461, 74.45764923095703, 74.83259582519531, 73.8877182006836, 76.45706939697266 75.68145751953125, 74.0724105834961, 75.38518524169922, 75.0858154296875, 74.6799087524414, 74.61680603027344 74.97571563720703, 76.26251983642578,

74.65586853027344,

```
75.06360626220703,

74.21228790283203,

74.95553588867188,

74.78788757324219,

76.54328918457031,

74.62157440185547,

74.059326171875,

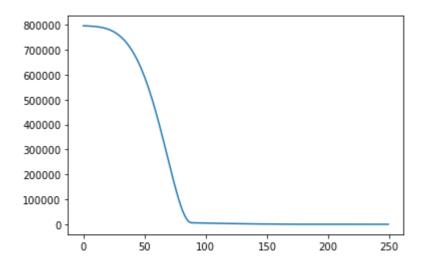
74.98696899414062]
```

In [25]:

```
sbn.lineplot(x=range(len(loss)),y=loss)
```

Out[25]:

<matplotlib.axes._subplots.AxesSubplot at 0x2427f4bf700>



In [26]:

type(loss)

Out[26]:

list

In [27]:

trainLoss = model.evaluate(x_train,y_train,verbose=0)

In [28]:

testLoss = model.evaluate(x_test,y_test,verbose=0)

In [29]:

trainLoss

Out[29]:

76.29065704345703

```
In [30]:
testLoss
```

Out[30]:

85.68230438232422

In [31]:

testPredictions = model.predict(x_test)

In [32]:

testPredictions

Out[32]:

```
array([[1075.712
       [ 622.3281 ],
       [ 874.28894],
       [ 892.3403 ],
       [ 897.5878 ],
       [ 450.19385],
       [ 929.2307 ],
         989.4385],
       [ 939.3156 ],
       [1014.7662],
       [ 749.278
       [ 916.0104 ],
       [ 945.5546 ],
       [1052.6495],
       [1119.3452],
       [ 679.97974],
       [1124.796
                  ],
       [ 649.3588 ],
       [1152.381
       [ 884.7037 ],
       [ 890.963
       [ 715.1833 ],
        455.60962],
       [ 610.50165],
       [ 833.24274],
       [1089.1198],
       [ 712.1501 ],
       [ 755.2
       [ 871.62726],
         768.91864],
       [ 449.9818 ],
       [ 781.36475],
       [ 726.64087],
       [ 645.2605 ],
       [ 884.8779 ],
       [ 842.00604],
       [1033.7091],
       [1020.7664],
       [ 843.1485 ],
       [ 860.3966 ],
       [ 755.4714 ],
       [1172.3597],
       [1095.503
       [1085.7281],
       [ 871.3757 ],
       [ 595.1567 ],
       [1143.5466],
       [ 971.1796 ],
       [1039.6761],
       [ 856.277
       [ 802.13043],
       [ 857.3641 ],
       [ 792.788
       [1009.5976],
       [1032.8241],
       [ 932.61804],
       [ 944.60455],
       [1073.53
                  ],
       [ 883.3702 ],
```

[1008.70514], [785.55426], 848.58545], [724.0116], [892.0331], 969.0759], 698.61346], [794.23425], [806.18805], [856.3295], [825.2129], [800.7238], 937.3497], [1057.5238], [944.2265], [987.72363], [665.79706], 637.74335], [696.8008], [877.29193], 905.8793], 979.3516], [987.0207], [611.56866], [861.1111], [621.5625], [957.27075], [827.2183], 894.4473], [872.96124], [630.6386], 794.9821], [708.0402], [1192.6935], [891.30365], 828.5504], [1099.2224], [852.0345], [964.027], 964.1813], [437.2963], [986.02234], [1061.1412], [878.8156], [1053.723 [560.77026], 662.17303], [855.9906], [710.03455], 918.4955], 924.2747], [718.33636], [882.4583], [978.5975], [1060.5543], [690.1289], 905.43317], 854.3602], [865.3591], [1030.1578], [784.2367],

[711.3574], [858.4811], [1128.8314], [798.4917], [822.7563], 896.0247], 773.60315], [930.93146], [961.81226], 920.18085], [944.9997], [1096.1127],[1029.7194], [799.397], [754.33514], [770.21783], 734.6377], 738.11774], [675.32947], [1134.6146], [647.8641], 979.3212], [705.8951], [893.0713], [986.0649], [604.07477], [739.5031], 784.5573], 866.2573], [744.5361], [555.61066], 634.533 [730.46893], [1053.2462], [1109.3221], [899.7554], [713.1508], [788.26636], [876.87823], 954.0809], [599.1237], 849.2331], 880.15155], 631.52374], [915.7882], [996.5247], [1183.7501], [802.7649], [738.40045], 959.61536], 714.0195], [1012.64276], [1224.743 [898.7332], [879.4742], [647.8354], [608.7238], 740.69366], 961.24335], [697.70807], [763.42883],

[813.78546], [690.6668], 919.79425], [870.6877], [610.6737], [1061.05 [944.25555], [1148.159], [784.42914], [877.9405], [655.8369], [666.32635], [732.29596], [681.04126], [1078.9698], [783.8185], [854.7622], [1142.8053], [583.6705], [955.32074], [659.94977], [568.44824], [747.83014], [594.3454], [1003.0618], [1031.3085], [630.28174], [936.61957], [826.3524], [1132.4084], [916.3311], [884.8854], [975.58734], [1034.5082], [876.70746], [850.1319], [835.75555], [651.66595], [1346.7157], 923.367 [531.1425], [794.6959], [989.4185], [853.9349], [790.76074], [677.5588], 787.38617], [971.14105], [917.1244], 996.41876], 943.3652], [903.2282], [741.61993], [1058.2197], [1137.7094], [1009.36096], [1011.918 [994.03424], [850.17615], [1007.924]], [625.38104],

[893.3743], [1065.3224], [780.00507], [566.5963], [605.58307], 989.15717], [876.4562], [1068.4766], 845.28516], 742.3365], 541.8187], [871.0722], 778.4855], [849.2774], [886.24896], [908.5151], [616.2292], [1018.77924], [627.30927], [882.72723], 795.3 914.7277], [965.1241], [786.0969], [876.7218], [1156.2091], [1007.0037], [846.9775], [1081.2754], [995.1761], [582.9196], [544.0256], [972.60504], [1044.842 [946.43256], 902.46625], [400.9013], [1016.2441], [914.8879], 818.0635], [933.122 [926.00055], 985.3576], 971.3304], [961.7828], 614.08124], 968.3708], 976.1457], [880.04047], 853.8068], 731.48444], [945.84894], [887.13544], 805.0572], 967.876 [831.8079], [1011.47064], [604.81647], 571.26544], [719.8318], [803.7181],

```
[ 885.36707],
[1220.1388],
[ 607.3808 ],
[1037.5138],
[ 663.2338 ],
[1125.7823],
[ 798.6256 ],
[1210.9335],
[ 785.4593 ],
[ 641.9009 ],
[ 891.3725 ],
[ 921.1593 ],
[ 842.51996],
[ 666.842
[ 987.80975],
[1089.0227],
[ 772.4516 ],
[ 895.2872 ],
[1055.7
[ 976.73267],
[ 708.64667],
[ 604.8831 ],
[1011.5636],
[ 789.07
[ 764.28937],
[1165.4045],
[ 800.98096]], dtype=float32)
```

In [33]:

```
predictionsDataFrame = pd.DataFrame(y_test,columns = ["Gerçek Fiyatlar"])
```

In [34]:

```
predictionsDataFrame
```

Out[34]:

Gerçek Fiyatlar 1081.652164 0 1 622.675990 2 889.356810 3 902.826733 4 897.662404 ... 325 1028.438035 326 789.934950 327 758.490486 328 1172.871659 329 820.947936

330 rows × 1 columns

In [35]:

```
testPredictions = pd.Series(testPredictions.reshape(330))
```

In [36]:

```
testPredictions
```

Out[36]:

```
0
       1075.712036
1
        622.328125
2
        874.288940
3
        892.340271
4
        897.587830
325
       1011.563599
326
       789.070007
327
       764.289368
328
       1165.404541
329
        800.980957
Length: 330, dtype: float32
```

In [37]:

```
predictionsDataFrame = pd.concat([predictionsDataFrame,testPredictions],axis=1)
```

In [38]:

predictionsDataFrame

Out[38]:

	Gerçek Fiyatlar	0
0	1081.652164	1075.712036
1	622.675990	622.328125
2	889.356810	874.288940
3	902.826733	892.340271
4	897.662404	897.587830
325	1028.438035	1011.563599
326	789.934950	789.070007
327	758.490486	764.289368
328	1172.871659	1165.404541
329	820.947936	800.980957

330 rows × 2 columns

In [39]:

```
predictionsDataFrame.columns=["Gerçek Fiyatlar","Tahmin Fiyatlar"]
```

In [40]:

predictionsDataFrame

Out[40]:

	Gerçek Fiyatlar	Tahmin Fiyatlar
0	1081.652164	1075.712036
1	622.675990	622.328125
2	889.356810	874.288940
3	902.826733	892.340271
4	897.662404	897.587830
325	1028.438035	1011.563599
326	789.934950	789.070007
327	758.490486	764.289368
328	1172.871659	1165.404541
329	820.947936	800.980957

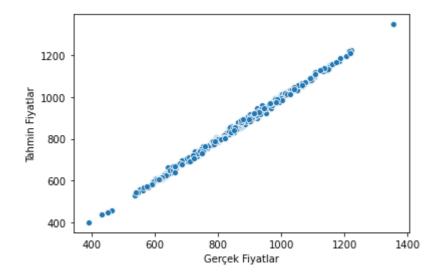
330 rows × 2 columns

In [41]:

sbn.scatterplot(x = "Gerçek Fiyatlar", y = "Tahmin Fiyatlar",data = predictionsDataFram
e)

Out[41]:

<matplotlib.axes._subplots.AxesSubplot at 0x2424de71190>



In [42]:

from sklearn.metrics import mean_absolute_error , mean_squared_error

```
In [43]:
```

mean_absolute_error(predictionsDataFrame["Gerçek Fiyatlar"],predictionsDataFrame["Tahmi
n Fiyatlar"])

Out[43]:

7.4341270166323365

In [44]:

mean_squared_error(predictionsDataFrame["Gerçek Fiyatlar"],predictionsDataFrame["Tahmin
Fiyatlar"])

Out[44]:

85.68224900699708

In [45]:

dataFrame.describe()

Out[45]:

	Fiyat	BisikletOzellik1	BisikletOzellik2
count	1000.000000	1000.000000	1000.000000
mean	872.677801	1750.024800	1749.964733
std	164.124504	1.704531	1.659578
min	390.856887	1744.852108	1744.742389
25%	757.795031	1748.831119	1748.803186
50%	879.168705	1750.017350	1750.003926
75%	988.612778	1751.115766	1751.129414
max	1355.213745	1755.613884	1754.666038

In [46]:

ortalaması 872 tl olan fiyatlarda 7tl sapma var

In [47]:

newVariable = [[1753,1751]]

In [48]:

newVariable = scaler.transform(newVariable)

In [49]:

newVariable

Out[49]:

array([[0.75368734, 0.62095915]])

12.03.2021

```
Tensorflow
In [50]:
model.predict(newVariable)
Out[50]:
array([[1081.0853]], dtype=float32)
Save Model
In [51]:
from tensorflow.keras.models import load_model
In [52]:
model.save("new_model.h5")
In [53]:
attachedModel = load_model("new_model.h5")
```

In [54]:

```
attachedModel.predict(newVariable)
```

Out[54]:

```
array([[1081.0853]], dtype=float32)
```

Car Price Analysis

```
In [55]:
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sbn
```

```
In [56]:
```

```
dataFrame = pd.read_excel("merc.xlsx")
```

In [57]:

dataFrame

Out[57]:

	year	price	transmission	mileage	tax	mpg	engineSize
0	2005	5200	Automatic	63000	325	32.1	1.8
1	2017	34948	Automatic	27000	20	61.4	2.1
2	2016	49948	Automatic	6200	555	28.0	5.5
3	2016	61948	Automatic	16000	325	30.4	4.0
4	2016	73948	Automatic	4000	325	30.1	4.0
13114	2020	35999	Automatic	500	145	55.4	2.0
13115	2020	24699	Automatic	2500	145	55.4	2.0
13116	2019	30999	Automatic	11612	145	41.5	2.1
13117	2019	37990	Automatic	2426	145	45.6	2.0
13118	2019	54999	Automatic	2075	145	52.3	2.9

13119 rows × 7 columns

In [58]:

dataFrame.describe()

Out[58]:

	year	price	mileage	tax	mpg	engineSize
count	13119.000000	13119.000000	13119.000000	13119.000000	13119.000000	13119.000000
mean	2017.296288	24698.596920	21949.559037	129.972178	55.155843	2.071530
std	2.224709	11842.675542	21176.512267	65.260286	15.220082	0.572426
min	1970.000000	650.000000	1.000000	0.000000	1.100000	0.000000
25%	2016.000000	17450.000000	6097.500000	125.000000	45.600000	1.800000
50%	2018.000000	22480.000000	15189.000000	145.000000	56.500000	2.000000
75%	2019.000000	28980.000000	31779.500000	145.000000	64.200000	2.100000
max	2020.000000	159999.000000	259000.000000	580.000000	217.300000	6.200000
4						•

In [59]:

```
dataFrame.isnull().sum()
```

Out[59]:

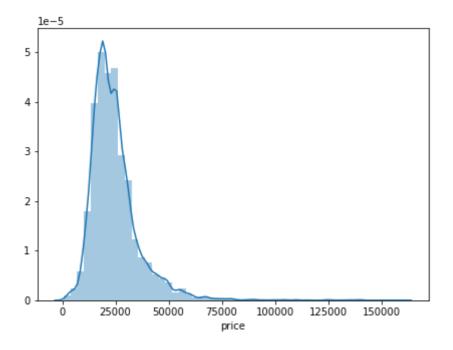
year 0
price 0
transmission 0
mileage 0
tax 0
mpg 0
engineSize 0
dtype: int64

In [60]:

```
plt.figure(figsize = (7,5))
sbn.distplot(dataFrame["price"])
```

Out[60]:

<matplotlib.axes._subplots.AxesSubplot at 0x24245f76850>

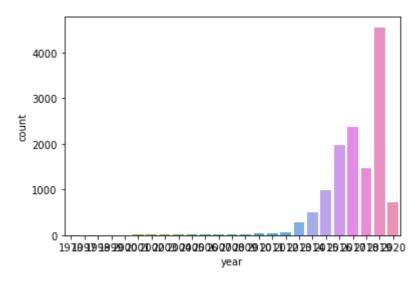


In [61]:

sbn.countplot(dataFrame["year"])

Out[61]:

<matplotlib.axes._subplots.AxesSubplot at 0x2424ddc5430>



In [62]:

dataFrame.corr()

Out[62]:

	year	price	mileage	tax	mpg	engineSize
year	1.000000	0.520712	-0.738027	0.012480	-0.094626	-0.142147
price	0.520712	1.000000	-0.537214	0.268717	-0.438445	0.516126
mileage	-0.738027	-0.537214	1.000000	-0.160223	0.202850	0.063652
tax	0.012480	0.268717	-0.160223	1.000000	-0.513742	0.338341
mpg	-0.094626	-0.438445	0.202850	-0.513742	1.000000	-0.339862
engineSize	-0.142147	0.516126	0.063652	0.338341	-0.339862	1.000000

In [63]:

dataFrame.corr()["price"].sort_values() # fiyatı etkileyen verilerin oranını görüyoruz

Out[63]:

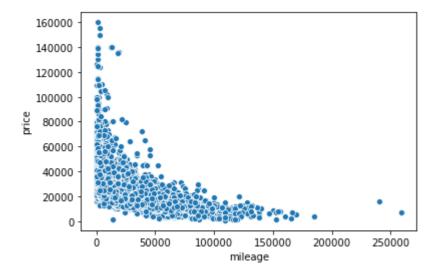
mileage -0.537214 mpg -0.438445 tax 0.268717 engineSize 0.516126 year 0.520712 price 1.000000 Name: price, dtype: float64

In [64]:

```
sbn.scatterplot(x ="mileage" , y ="price" , data=dataFrame)
```

Out[64]:

<matplotlib.axes._subplots.AxesSubplot at 0x2424f684040>

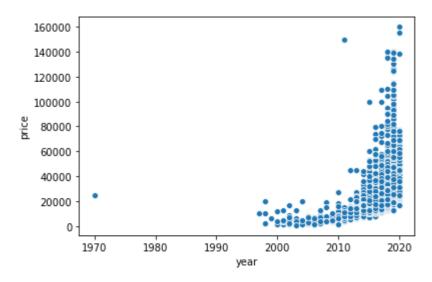


In [65]:

```
sbn.scatterplot(x ="year" , y ="price" , data=dataFrame)
```

Out[65]:

<matplotlib.axes._subplots.AxesSubplot at 0x2424f6b7fa0>



In [66]:

```
dataFrame.sort_values("price",ascending = True).head(20)
```

Out[66]:

	year	price	transmission	mileage	tax	mpg	engineSize
11816	2003	650	Manual	109090	235	40.0	1.4
12008	2010	1350	Manual	116126	145	54.3	2.0
11765	2000	1490	Automatic	87000	265	27.2	3.2
11549	2002	1495	Automatic	13800	305	39.8	2.7
12594	2004	1495	Manual	119000	300	34.5	1.8
11174	2001	1695	Automatic	108800	325	31.7	3.2
12710	2006	1695	Automatic	153000	300	33.6	1.8
12766	2004	1780	Automatic	118000	265	41.5	2.2
12009	2007	1800	Automatic	84000	200	42.8	1.5
11764	1998	1990	Automatic	99300	265	32.1	2.3
11808	1998	1990	Automatic	113557	265	32.1	2.3
11383	2005	1995	Automatic	105000	260	43.5	2.1
11378	2004	1995	Semi-Auto	165000	330	20.0	3.7
11857	2002	2140	Automatic	52700	325	31.4	2.0
11906	2007	2478	Automatic	81000	160	49.6	2.0
11795	2005	2490	Automatic	101980	200	47.9	2.0
12765	2004	2495	Automatic	104000	325	31.7	1.8
11943	2005	2690	Automatic	109000	325	32.1	1.8
11263	2007	2795	Manual	79485	200	45.6	1.5
49	2006	2880	Automatic	66000	160	52.3	2.0

In [67]:

len(dataFrame)

Out[67]:

13119

In [68]:

13119 * 0.01

Out[68]:

131.19

In [69]:

nineNinePercentdataFrame = dataFrame.sort_values("price",ascending=False).iloc[131:]

In [70]:

nineNinePercentdataFrame #veri setini bozan az sayıda pahalı araba veri setinden atıld ı.

Out[70]:

	year	price	transmission	mileage	tax	mpg	engineSize
6177	2019	65990	Semi-Auto	5076	150	30.4	3.0
5779	2020	65990	Semi-Auto	999	145	28.0	4.0
3191	2020	65980	Semi-Auto	3999	145	28.0	4.0
4727	2019	65000	Semi-Auto	3398	145	27.2	4.0
8814	2019	64999	Semi-Auto	119	145	40.9	3.0
11549	2002	1495	Automatic	13800	305	39.8	2.7
12594	2004	1495	Manual	119000	300	34.5	1.8
11765	2000	1490	Automatic	87000	265	27.2	3.2
12008	2010	1350	Manual	116126	145	54.3	2.0
11816	2003	650	Manual	109090	235	40.0	1.4

12988 rows × 7 columns

In [71]:

nineNinePercentdataFrame.describe()

Out[71]:

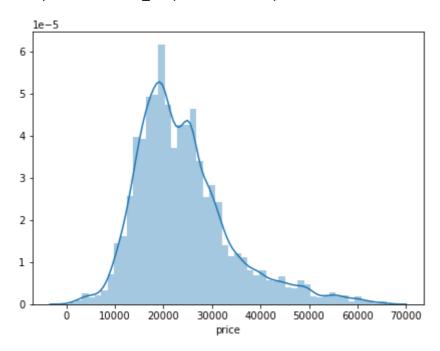
	year	price	mileage	tax	mpg	engineSize
count	12988.000000	12988.000000	12988.000000	12988.000000	12988.000000	12988.000000
mean	2017.281876	24074.926933	22132.741146	129.689714	55.437142	2.050901
std	2.228515	9866.224575	21196.776401	65.183076	15.025999	0.532596
min	1970.000000	650.000000	1.000000	0.000000	1.100000	0.000000
25%	2016.000000	17357.500000	6322.000000	125.000000	45.600000	1.675000
50%	2018.000000	22299.000000	15369.500000	145.000000	56.500000	2.000000
75%	2019.000000	28706.000000	31982.250000	145.000000	64.200000	2.100000
max	2020.000000	65990.000000	259000.000000	580.000000	217.300000	6.200000
4)

In [72]:

```
plt.figure(figsize=(7,5))
sbn.distplot(nineNinePercentdataFrame["price"])
```

Out[72]:

<matplotlib.axes._subplots.AxesSubplot at 0x242465135b0>



In [73]:

```
dataFrame.groupby("year").mean()["price"]
```

Out[73]:

```
year
1970
        24999.000000
1997
         9995.000000
1998
         8605.000000
1999
         5995.000000
2000
         5743.333333
2001
         4957.900000
2002
         5820.444444
2003
         4878.000000
2004
         4727.615385
2005
         4426.111111
2006
         4036.875000
2007
         5136.045455
2008
         6967.437500
2009
         6166.764706
2010
         8308.473684
2011
        12624.894737
2012
        10845.140351
2013
        11939.842466
2014
        14042.936864
2015
        16731.780020
2016
        19307.892948
2017
        21514.307854
2018
        25720.162918
2019
        31290.020865
2020
        35433.282337
Name: price, dtype: float64
```

In [74]:

nineNinePercentdataFrame.groupby("year").mean()["price"]

Out[74]:

```
year
1970
        24999.000000
1997
         9995.000000
1998
         8605.000000
1999
         5995.000000
2000
         5743.333333
2001
         4957.900000
2002
         5820.444444
2003
         4878.000000
2004
         4727.615385
2005
         4426.111111
2006
         4036.875000
2007
         5136.045455
2008
         6967.437500
2009
         6166.764706
2010
         8308.473684
2011
         8913.459459
2012
        10845.140351
2013
        11939.842466
2014
        14042.936864
        16647.822222
2015
2016
        19223.558943
2017
        21356.280421
2018
        24800.844506
2019
        30289.524832
2020
        34234.794872
Name: price, dtype: float64
```

In [75]:

```
dataFrame[dataFrame.year != 1970].groupby("year").mean()["price"]
```

Out[75]:

```
year
1997
         9995.000000
1998
         8605.000000
1999
         5995.000000
2000
         5743.333333
2001
         4957.900000
2002
         5820.444444
2003
         4878.000000
2004
         4727.615385
2005
         4426.111111
2006
         4036.875000
2007
         5136.045455
2008
         6967.437500
2009
         6166.764706
2010
         8308.473684
        12624.894737
2011
2012
        10845.140351
2013
        11939.842466
2014
        14042.936864
2015
        16731.780020
2016
        19307.892948
2017
        21514.307854
2018
        25720.162918
2019
        31290.020865
2020
        35433.282337
```

Name: price, dtype: float64

In [76]:

```
dataFrame = nineNinePercentdataFrame
```

In [77]:

dataFrame.describe()

Out[77]:

	year	price	mileage	tax	mpg	engineSize
count	12988.000000	12988.000000	12988.000000	12988.000000	12988.000000	12988.000000
mean	2017.281876	24074.926933	22132.741146	129.689714	55.437142	2.050901
std	2.228515	9866.224575	21196.776401	65.183076	15.025999	0.532596
min	1970.000000	650.000000	1.000000	0.000000	1.100000	0.000000
25%	2016.000000	17357.500000	6322.000000	125.000000	45.600000	1.675000
50%	2018.000000	22299.000000	15369.500000	145.000000	56.500000	2.000000
75%	2019.000000	28706.000000	31982.250000	145.000000	64.200000	2.100000
max	2020.000000	65990.000000	259000.000000	580.000000	217.300000	6.200000
4						•

In [78]:

```
dataFrame = dataFrame[dataFrame.year != 1970]
```

In [79]:

```
dataFrame.groupby("year").mean()["price"]
```

Out[79]:

year 1997 9995.000000 1998 8605.000000 1999 5995.000000 2000 5743.333333 2001 4957.900000 2002 5820.444444 2003 4878.000000 2004 4727.615385 2005 4426.111111 2006 4036.875000 2007 5136.045455 2008 6967.437500 2009 6166.764706 2010 8308.473684 2011 8913.459459 2012 10845.140351 2013 11939.842466 2014 14042.936864 2015 16647.822222 2016 19223.558943 2017 21356.280421 2018 24800.844506 2019 30289.524832 2020 34234.794872

Name: price, dtype: float64

In [80]:

dataFrame.head()

Out[80]:

	year	price	transmission	mileage	tax	mpg	engineSize
6177	2019	65990	Semi-Auto	5076	150	30.4	3.0
5779	2020	65990	Semi-Auto	999	145	28.0	4.0
3191	2020	65980	Semi-Auto	3999	145	28.0	4.0
4727	2019	65000	Semi-Auto	3398	145	27.2	4.0
8814	2019	64999	Semi-Auto	119	145	40.9	3.0

In [81]:

dataFrame = dataFrame.drop("transmission",axis = 1) #sayısal olmayan verileri hata oluş
masın diye sildik

```
In [82]:
```

```
dataFrame
```

Out[82]:

	year	price	mileage	tax	mpg	engineSize
6177	2019	65990	5076	150	30.4	3.0
5779	2020	65990	999	145	28.0	4.0
3191	2020	65980	3999	145	28.0	4.0
4727	2019	65000	3398	145	27.2	4.0
8814	2019	64999	119	145	40.9	3.0
11549	2002	1495	13800	305	39.8	2.7
12594	2004	1495	119000	300	34.5	1.8
11765	2000	1490	87000	265	27.2	3.2
12008	2010	1350	116126	145	54.3	2.0
11816	2003	650	109090	235	40.0	1.4

12987 rows × 6 columns

```
In [83]:
```

```
y = dataFrame["price"].values
x = dataFrame.drop("price",axis=1).values
```

In [84]:

```
у
```

Out[84]:

```
array([65990, 65990, 65980, ..., 1490, 1350, 650], dtype=int64)
```

In [85]:

```
x
```

Out[85]:

```
array([[2.01900e+03, 5.07600e+03, 1.50000e+02, 3.04000e+01, 3.00000e+00], [2.02000e+03, 9.99000e+02, 1.45000e+02, 2.80000e+01, 4.00000e+00], [2.02000e+03, 3.99900e+03, 1.45000e+02, 2.80000e+01, 4.00000e+00], ..., [2.00000e+03, 8.70000e+04, 2.65000e+02, 2.72000e+01, 3.20000e+00], [2.01000e+03, 1.16126e+05, 1.45000e+02, 5.43000e+01, 2.00000e+00], [2.00300e+03, 1.09090e+05, 2.35000e+02, 4.00000e+01, 1.40000e+00]])
```

In [86]:

```
from sklearn.model_selection import train_test_split
```

```
In [87]:
x_train , x_test , y_train, y_test = train_test_split(x, y, test_size=0.3, random_state
= 10)
In [88]:
len(x_train)
Out[88]:
9090
In [89]:
len(x_test)
Out[89]:
3897
In [90]:
from sklearn.preprocessing import MinMaxScaler
In [91]:
scaler = MinMaxScaler()
In [92]:
x train = scaler.fit transform(x train)
x_test = scaler.fit_transform(x_test)
In [93]:
x_train
Out[93]:
array([[0.82608696, 0.07228985, 0.03448276, 0.30619796, 0.33870968],
                                        , 0.27890842, 0.32258065],
       [0.86956522, 0.22407036, 0.25
       [0.82608696, 0.11663365, 0.05172414, 0.29879741, 0.32258065],
       . . . ,
       [0.65217391, 0.25115541, 0.21551724, 0.27890842, 0.29032258],
       [0.73913043, 0.11981513, 0.34482759, 0.18408881, 0.32258065],
       [0.86956522, 0.06027436, 0.40517241, 0.20212766, 0.35483871]])
In [94]:
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
In [95]:
x_train.shape
Out[95]:
(9090, 5)
```

In [96]:

```
model = Sequential()

model.add(Dense(12,activation = "relu")) #nöronlar
model.add(Dense(12,activation = "relu"))
model.add(Dense(12,activation = "relu"))
model.add(Dense(12,activation = "relu"))

model.add(Dense(1)) #çıkış katmanı

model.compile(optimizer = "adam",loss="mse")
```

In [97]:

model.fit(x = x_train, y = y_train, validation_data = (x_test,y_test), batch_size = 250, epochs = 300)

```
Epoch 1/300
05 - val loss: 688066496.0000
Epoch 2/300
6 - val loss: 687933120.0000
Epoch 3/300
00 - val loss: 687504064.0000
Epoch 4/300
74 - val loss: 686210496.0000
Epoch 5/300
1 - val_loss: 682975872.0000
Epoch 6/300
9 - val_loss: 675948032.0000
Epoch 7/300
37 - val_loss: 662304256.0000
Epoch 8/300
6 - val_loss: 638261120.0000
Epoch 9/300
89 - val_loss: 599629888.0000
Epoch 10/300
0 - val_loss: 542429120.0000
Epoch 11/300
9 - val_loss: 465476544.0000
Epoch 12/300
0 - val_loss: 372496768.0000
Epoch 13/300
7 - val_loss: 274934944.0000
Epoch 14/300
3 - val loss: 189339856.0000
Epoch 15/300
37/37 [============] - Øs 9ms/step - loss: 168799375.157
9 - val loss: 131952984.0000
Epoch 16/300
8 - val_loss: 105265568.0000
Epoch 17/300
- val loss: 96697488.0000
Epoch 18/300
- val loss: 94343072.0000
Epoch 19/300
- val loss: 93308952.0000
Epoch 20/300
5 - val loss: 92507392.0000
Epoch 21/300
```

```
8 - val_loss: 91761760.0000
Epoch 22/300
- val loss: 91028552.0000
Epoch 23/300
- val_loss: 90349496.0000
Epoch 24/300
8 - val_loss: 89701800.0000
Epoch 25/300
7 - val_loss: 89061936.0000
Epoch 26/300
7 - val_loss: 88417208.0000
Epoch 27/300
- val_loss: 87805240.0000
Epoch 28/300
- val_loss: 87209208.0000
Epoch 29/300
- val_loss: 86603216.0000
Epoch 30/300
- val loss: 86045216.0000
Epoch 31/300
5 - val_loss: 85467704.0000
Epoch 32/300
6 - val_loss: 84899728.0000
Epoch 33/300
- val_loss: 84329448.0000
Epoch 34/300
- val loss: 83757608.0000
Epoch 35/300
37/37 [============== ] - 0s 8ms/step - loss: 80726828.0000
- val_loss: 83215912.0000
Epoch 36/300
37/37 [=============== ] - Os 7ms/step - loss: 80347079.1579
- val loss: 82651544.0000
Epoch 37/300
- val_loss: 82090488.0000
Epoch 38/300
- val loss: 81604504.0000
Epoch 39/300
- val_loss: 81040960.0000
Epoch 40/300
- val loss: 80518320.0000
Epoch 41/300
```

```
- val_loss: 79958792.0000
Epoch 42/300
37/37 [=============== ] - 0s 7ms/step - loss: 79446229.4737
- val loss: 79444128.0000
Epoch 43/300
- val_loss: 78897920.0000
Epoch 44/300
- val loss: 78363752.0000
Epoch 45/300
- val_loss: 77851288.0000
Epoch 46/300
- val loss: 77294264.0000
Epoch 47/300
- val_loss: 76776296.0000
Epoch 48/300
- val_loss: 76243920.0000
Epoch 49/300
- val_loss: 75707248.0000
Epoch 50/300
- val_loss: 75180008.0000
Epoch 51/300
- val loss: 74643256.0000
Epoch 52/300
- val loss: 74071304.0000
Epoch 53/300
- val_loss: 73588240.0000
Epoch 54/300
- val loss: 73029968.0000
Epoch 55/300
- val loss: 72433976.0000
Epoch 56/300
- val loss: 71946120.0000
Epoch 57/300
37/37 [============= ] - 0s 5ms/step - loss: 71541169.8947
- val loss: 71397016.0000
Epoch 58/300
- val loss: 70835520.0000
Epoch 59/300
- val_loss: 70279176.0000
Epoch 60/300
- val loss: 69797968.0000
Epoch 61/300
- val_loss: 69238456.0000
```

```
Epoch 62/300
- val_loss: 68659776.0000
Epoch 63/300
- val_loss: 68028208.0000
Epoch 64/300
- val_loss: 67576632.0000
Epoch 65/300
- val_loss: 66964748.0000
Epoch 66/300
- val loss: 66411992.0000
Epoch 67/300
- val loss: 65851100.0000
Epoch 68/300
- val loss: 65224780.0000
Epoch 69/300
- val_loss: 64628376.0000
Epoch 70/300
- val loss: 64097312.0000
Epoch 71/300
- val_loss: 63542480.0000
Epoch 72/300
- val_loss: 62866732.0000
Epoch 73/300
- val_loss: 62259256.0000
Epoch 74/300
- val_loss: 61766956.0000
Epoch 75/300
- val loss: 61040780.0000
Epoch 76/300
- val_loss: 60383448.0000
Epoch 77/300
- val loss: 59874136.0000
Epoch 78/300
- val loss: 59137772.0000
Epoch 79/300
8 - val loss: 58590628.0000
Epoch 80/300
- val loss: 57791772.0000
Epoch 81/300
3 - val loss: 57148820.0000
Epoch 82/300
```

```
- val_loss: 56460436.0000
Epoch 83/300
- val loss: 55854984.0000
Epoch 84/300
- val_loss: 55125444.0000
Epoch 85/300
- val_loss: 54420564.0000
Epoch 86/300
- val_loss: 53786664.0000
Epoch 87/300
- val_loss: 52946120.0000
Epoch 88/300
- val_loss: 52233968.0000
Epoch 89/300
- val_loss: 51595596.0000
Epoch 90/300
- val_loss: 50851960.0000
Epoch 91/300
- val loss: 50171896.0000
Epoch 92/300
- val_loss: 49385264.0000
Epoch 93/300
- val_loss: 48554996.0000
Epoch 94/300
- val_loss: 47842148.0000
Epoch 95/300
- val loss: 46974552.0000
Epoch 96/300
37/37 [============== ] - 0s 8ms/step - loss: 49649718.3158
- val_loss: 46453112.0000
Epoch 97/300
- val loss: 45656488.0000
Epoch 98/300
- val_loss: 44727916.0000
Epoch 99/300
- val loss: 44031704.0000
Epoch 100/300
- val_loss: 43380468.0000
Epoch 101/300
- val loss: 42786852.0000
Epoch 102/300
```

```
- val_loss: 42181804.0000
Epoch 103/300
37/37 [=============== ] - 0s 7ms/step - loss: 43470478.0000
- val loss: 41147460.0000
Epoch 104/300
- val_loss: 40479832.0000
Epoch 105/300
- val loss: 40240856.0000
Epoch 106/300
37/37 [============== ] - 0s 4ms/step - loss: 41531413.7895
- val_loss: 39419192.0000
Epoch 107/300
- val loss: 38947432.0000
Epoch 108/300
- val_loss: 37972500.0000
Epoch 109/300
- val_loss: 37852408.0000
Epoch 110/300
- val_loss: 37214628.0000
Epoch 111/300
- val_loss: 37017020.0000
Epoch 112/300
- val_loss: 36311336.0000
Epoch 113/300
- val loss: 35942196.0000
Epoch 114/300
- val_loss: 35546760.0000
Epoch 115/300
- val_loss: 34742488.0000
Epoch 116/300
- val_loss: 35731540.0000
Epoch 117/300
37/37 [================ ] - Os 7ms/step - loss: 33189201.5789
- val loss: 34443020.0000
Epoch 118/300
val loss: 34245872.0000
Epoch 119/300
- val loss: 34332084.0000
Epoch 120/300
- val_loss: 33433230.0000
Epoch 121/300
- val loss: 33786028.0000
Epoch 122/300
- val_loss: 33155958.0000
```

```
Epoch 123/300
- val loss: 32915492.0000
Epoch 124/300
- val_loss: 32419224.0000
Epoch 125/300
- val loss: 32002080.0000
Epoch 126/300
- val_loss: 31732506.0000
Epoch 127/300
- val loss: 31665050.0000
Epoch 128/300
- val loss: 31516534.0000
Epoch 129/300
- val loss: 31808374.0000
Epoch 130/300
- val_loss: 30901856.0000
Epoch 131/300
37/37 [============= ] - 0s 4ms/step - loss: 27158367.4737
- val loss: 30855646.0000
Epoch 132/300
- val_loss: 30836334.0000
Epoch 133/300
- val_loss: 30903634.0000
Epoch 134/300
- val_loss: 30140000.0000
Epoch 135/300
- val_loss: 29803140.0000
Epoch 136/300
- val loss: 29227416.0000
Epoch 137/300
- val_loss: 29199034.0000
Epoch 138/300
- val_loss: 29104574.0000
Epoch 139/300
- val loss: 28936986.0000
Epoch 140/300
- val loss: 29015742.0000
Epoch 141/300
37/37 [============= ] - 0s 3ms/step - loss: 24557397.7368
- val loss: 28544056.0000
Epoch 142/300
val loss: 28296142.0000
Epoch 143/300
```

```
- val loss: 28405456.0000
Epoch 144/300
- val loss: 27510158.0000
Epoch 145/300
- val_loss: 27343710.0000
Epoch 146/300
- val_loss: 27074970.0000
Epoch 147/300
- val_loss: 26900168.0000
Epoch 148/300
- val_loss: 27663920.0000
Epoch 149/300
- val_loss: 27271910.0000
Epoch 150/300
- val_loss: 27054170.0000
Epoch 151/300
- val_loss: 27104130.0000
Epoch 152/300
37/37 [============== ] - 0s 3ms/step - loss: 23279669.8421
- val loss: 27239668.0000
Epoch 153/300
- val_loss: 27050880.0000
Epoch 154/300
- val_loss: 27065284.0000
Epoch 155/300
- val_loss: 27196086.0000
Epoch 156/300
- val loss: 26850780.0000
Epoch 157/300
37/37 [============= ] - 0s 3ms/step - loss: 21379080.7895
- val_loss: 26589370.0000
Epoch 158/300
37/37 [============== ] - 0s 3ms/step - loss: 22139247.0000
- val loss: 26466124.0000
Epoch 159/300
- val_loss: 26884098.0000
Epoch 160/300
- val loss: 26243744.0000
Epoch 161/300
- val_loss: 26188788.0000
Epoch 162/300
- val loss: 26683526.0000
Epoch 163/300
```

```
- val_loss: 26124988.0000
Epoch 164/300
- val_loss: 26789624.0000
Epoch 165/300
- val_loss: 25781790.0000
Epoch 166/300
- val loss: 26118330.0000
Epoch 167/300
37/37 [============= ] - 0s 4ms/step - loss: 21771350.9737
- val_loss: 25810424.0000
Epoch 168/300
37/37 [============== ] - 0s 4ms/step - loss: 21745394.6842
- val loss: 26430786.0000
Epoch 169/300
- val_loss: 25887596.0000
Epoch 170/300
- val_loss: 25599140.0000
Epoch 171/300
- val_loss: 25150252.0000
Epoch 172/300
- val_loss: 25210790.0000
Epoch 173/300
- val_loss: 25433278.0000
Epoch 174/300
- val loss: 25382476.0000
Epoch 175/300
- val_loss: 25682158.0000
Epoch 176/300
- val_loss: 25164638.0000
Epoch 177/300
- val_loss: 24930478.0000
Epoch 178/300
- val loss: 24877552.0000
Epoch 179/300
37/37 [============= ] - 0s 7ms/step - loss: 20735911.9474
val loss: 25112622.0000
Epoch 180/300
- val loss: 25646588.0000
Epoch 181/300
- val_loss: 25068616.0000
Epoch 182/300
- val loss: 25192534.0000
Epoch 183/300
- val_loss: 24938072.0000
```

```
Epoch 184/300
- val loss: 24657316.0000
Epoch 185/300
37/37 [============== ] - 0s 8ms/step - loss: 20562128.5789
- val_loss: 24866258.0000
Epoch 186/300
- val loss: 24476912.0000
Epoch 187/300
- val_loss: 24664840.0000
Epoch 188/300
- val loss: 24781670.0000
Epoch 189/300
- val loss: 25450672.0000
Epoch 190/300
- val loss: 24743434.0000
Epoch 191/300
- val_loss: 24922922.0000
Epoch 192/300
37/37 [============== ] - 0s 5ms/step - loss: 20609045.2632
- val loss: 25085086.0000
Epoch 193/300
- val_loss: 24199900.0000
Epoch 194/300
- val_loss: 25019910.0000
Epoch 195/300
- val_loss: 24819090.0000
Epoch 196/300
- val_loss: 24153310.0000
Epoch 197/300
- val loss: 24402464.0000
Epoch 198/300
37/37 [============== ] - 0s 6ms/step - loss: 20294984.7368
- val loss: 24020386.0000
Epoch 199/300
- val_loss: 25038836.0000
Epoch 200/300
- val loss: 24408900.0000
Epoch 201/300
- val loss: 24942476.0000
Epoch 202/300
37/37 [============= ] - 0s 4ms/step - loss: 20953297.8947
- val loss: 24182408.0000
Epoch 203/300
val loss: 24660770.0000
Epoch 204/300
```

```
- val_loss: 24292722.0000
Epoch 205/300
- val loss: 23931222.0000
Epoch 206/300
- val_loss: 24563140.0000
Epoch 207/300
- val_loss: 24821710.0000
Epoch 208/300
- val_loss: 24290184.0000
Epoch 209/300
- val_loss: 24216374.0000
Epoch 210/300
- val_loss: 24209074.0000
Epoch 211/300
- val_loss: 24633398.0000
Epoch 212/300
- val_loss: 24183632.0000
Epoch 213/300
37/37 [============== ] - 0s 4ms/step - loss: 19965365.6842
- val loss: 24229310.0000
Epoch 214/300
- val_loss: 24159614.0000
Epoch 215/300
- val_loss: 23812796.0000
Epoch 216/300
- val_loss: 23624066.0000
Epoch 217/300
- val loss: 24254506.0000
Epoch 218/300
- val_loss: 24402924.0000
Epoch 219/300
- val loss: 23819978.0000
Epoch 220/300
- val_loss: 24174502.0000
Epoch 221/300
- val loss: 24438254.0000
Epoch 222/300
- val_loss: 24366040.0000
Epoch 223/300
- val_loss: 23825272.0000
Epoch 224/300
```

```
- val_loss: 24143180.0000
Epoch 225/300
37/37 [============== ] - 0s 6ms/step - loss: 19434284.5789
- val_loss: 23868712.0000
Epoch 226/300
- val_loss: 23880224.0000
Epoch 227/300
- val loss: 24196378.0000
Epoch 228/300
37/37 [============= ] - 0s 7ms/step - loss: 19979469.0000
- val_loss: 24179416.0000
Epoch 229/300
37/37 [============== ] - 0s 5ms/step - loss: 19496286.0000
- val loss: 24480660.0000
Epoch 230/300
- val_loss: 24035748.0000
Epoch 231/300
- val_loss: 23942306.0000
Epoch 232/300
- val_loss: 23928662.0000
Epoch 233/300
- val_loss: 23607614.0000
Epoch 234/300
- val loss: 23806966.0000
Epoch 235/300
- val loss: 23555470.0000
Epoch 236/300
- val_loss: 23770830.0000
Epoch 237/300
- val_loss: 23543268.0000
Epoch 238/300
- val_loss: 23528188.0000
Epoch 239/300
- val loss: 23648792.0000
Epoch 240/300
37/37 [============== ] - 0s 4ms/step - loss: 19883645.8947
val loss: 24172862.0000
Epoch 241/300
- val loss: 23845676.0000
Epoch 242/300
- val_loss: 23178864.0000
Epoch 243/300
- val loss: 23352558.0000
Epoch 244/300
- val_loss: 23529356.0000
```

```
Epoch 245/300
- val loss: 23458968.0000
Epoch 246/300
- val_loss: 23661866.0000
Epoch 247/300
- val loss: 22954690.0000
Epoch 248/300
- val_loss: 23823446.0000
Epoch 249/300
- val loss: 23666412.0000
Epoch 250/300
- val loss: 23378862.0000
Epoch 251/300
- val loss: 23777066.0000
Epoch 252/300
- val_loss: 23343132.0000
Epoch 253/300
37/37 [============== ] - 0s 4ms/step - loss: 19176574.0526
- val loss: 22709830.0000
Epoch 254/300
- val_loss: 23471472.0000
Epoch 255/300
- val_loss: 23419870.0000
Epoch 256/300
- val_loss: 23374628.0000
Epoch 257/300
- val_loss: 23399406.0000
Epoch 258/300
- val loss: 23200228.0000
Epoch 259/300
37/37 [============= ] - 0s 4ms/step - loss: 19355422.5789
- val_loss: 22930048.0000
Epoch 260/300
- val_loss: 23773830.0000
Epoch 261/300
- val loss: 23143088.0000
Epoch 262/300
- val loss: 23354164.0000
Epoch 263/300
37/37 [============= ] - 0s 4ms/step - loss: 19972572.7895
- val loss: 24339592.0000
Epoch 264/300
val loss: 22923444.0000
Epoch 265/300
```

```
- val_loss: 23011660.0000
Epoch 266/300
37/37 [=============== ] - Os 3ms/step - loss: 19236433.1579
- val loss: 22936702.0000
Epoch 267/300
- val_loss: 23115878.0000
Epoch 268/300
- val_loss: 23383474.0000
Epoch 269/300
- val_loss: 23855194.0000
Epoch 270/300
- val_loss: 23502226.0000
Epoch 271/300
- val_loss: 22985616.0000
Epoch 272/300
- val_loss: 23112972.0000
Epoch 273/300
- val_loss: 23272784.0000
Epoch 274/300
- val loss: 22990644.0000
Epoch 275/300
- val_loss: 23186858.0000
Epoch 276/300
- val_loss: 23417340.0000
Epoch 277/300
- val_loss: 23305428.0000
Epoch 278/300
- val loss: 23110308.0000
Epoch 279/300
- val_loss: 23063150.0000
Epoch 280/300
- val loss: 22963722.0000
Epoch 281/300
- val_loss: 23765068.0000
Epoch 282/300
- val loss: 23372226.0000
Epoch 283/300
- val_loss: 23538444.0000
Epoch 284/300
- val_loss: 23436574.0000
Epoch 285/300
```

```
- val loss: 23654328.0000
Epoch 286/300
- val_loss: 23035518.0000
Epoch 287/300
- val_loss: 23077656.0000
Epoch 288/300
- val loss: 23033450.0000
Epoch 289/300
37/37 [============= ] - 0s 3ms/step - loss: 19707453.2105
- val_loss: 23796946.0000
Epoch 290/300
- val loss: 23007912.0000
Epoch 291/300
- val_loss: 22748644.0000
Epoch 292/300
- val loss: 22894260.0000
Epoch 293/300
- val_loss: 23146254.0000
Epoch 294/300
- val_loss: 22885442.0000
Epoch 295/300
- val loss: 23071924.0000
Epoch 296/300
- val loss: 22712600.0000
Epoch 297/300
- val_loss: 22985930.0000
Epoch 298/300
- val loss: 22704872.0000
Epoch 299/300
- val loss: 23032408.0000
Epoch 300/300
- val loss: 22481506.0000
```

Out[97]:

<tensorflow.python.keras.callbacks.History at 0x2424f7f20d0>

In [98]:

```
lossData = pd.DataFrame(model.history.history)
```

In [99]:

lossData.head()

Out[99]:

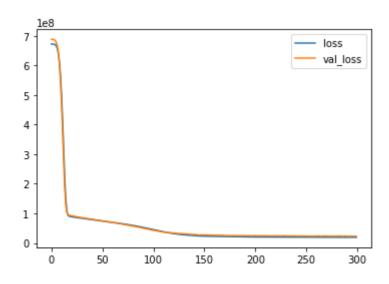
	loss	val_loss
0	672126592.0	688066496.0
1	672052672.0	687933120.0
2	671812480.0	687504064.0
3	671056128.0	686210496.0
4	669006336.0	682975872.0

In [100]:

lossData.plot()

Out[100]:

<matplotlib.axes._subplots.AxesSubplot at 0x24250ea7dc0>



In [101]:

from sklearn.metrics import mean_squared_error ,mean_absolute_error

In [102]:

predictionsArray = model.predict(x_test)

In [103]:

```
predictionsArray
```

```
Out[103]:
```

In [104]:

```
mean_absolute_error(y_test,predictionsArray) # 3418 paund fiyat sapması var.
```

Out[104]:

3345.902733454069

In [105]:

```
dataFrame.describe()
```

Out[105]:

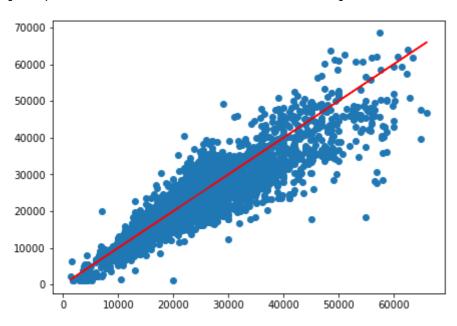
	year	price	mileage	tax	mpg	engineSize
count	12987.000000	12987.000000	12987.000000	12987.000000	12987.000000	12987.000000
mean	2017.285516	24074.855779	22133.367367	129.676215	55.438392	2.051059
std	2.189633	9866.601115	21197.472376	65.167429	15.025902	0.532313
min	1997.000000	650.000000	1.000000	0.000000	1.100000	0.000000
25%	2016.000000	17355.000000	6320.000000	125.000000	45.600000	1.700000
50%	2018.000000	22299.000000	15371.000000	145.000000	56.500000	2.000000
75%	2019.000000	28706.000000	31986.500000	145.000000	64.200000	2.100000
max	2020.000000	65990.000000	259000.000000	580.000000	217.300000	6.200000
4						•

In [106]:

```
plt.figure(figsize=(7,5))
plt.scatter(y_test,predictionsArray)
plt.plot(y_test,y_test,"r")
```

Out[106]:

[<matplotlib.lines.Line2D at 0x2425102c370>]



In [107]:

```
dataFrame.iloc[2]
```

Out[107]:

year	2020.0
price	65980.0
mileage	3999.0
tax	145.0
mpg	28.0
engineSize	4.0
Name: 3191,	dtype: float64

In [108]:

```
newCarSeries = dataFrame.drop("price",axis=1).iloc[2]
```

```
In [109]:
```

```
newCarSeries
```

Out[109]:

year 2020.0 mileage 3999.0 tax 145.0 mpg 28.0 engineSize 4.0

Name: 3191, dtype: float64

In [110]:

```
newCarSeries = scaler.transform(newCarSeries.values.reshape(-1,5))
```

In [111]:

```
model.predict(newCarSeries)
```

Out[111]:

array([[62372.]], dtype=float32)

Classification Problems

In [112]:

```
import pandas as pd
import numpy as np
```

In [113]:

```
dataFrame = pd.read_excel("maliciousornot.xlsx")
```

In [114]:

dataFrame

Out[114]:

	Туре	URL_LENGTH	NUMBER_SPECIAL_CHARACTERS	TCP_CONVERSATION_EXCHANG
0	1	23.303047	13.445560	159.06693
1	1	26.645007	23.018073	172.14980
2	1	25.505113	27.525833	168.39333
3	1	14.792707	26.398893	100.49196
4	1	26.282313	18.575080	174.99953
543	1	27.927387	29.002513	183.93733
544	1	26.075060	36.593167	169.94773
545	1	21.502533	36.372960	140.28460
546	1	26.683867	37.992127	181.47620
547	0	10.051787	31.787480	62.07237

548 rows × 31 columns

In [115]:

```
dataFrame.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 548 entries, 0 to 547
Data columns (total 31 columns):

pata #	Columns (total 31 Columns)		Dtypo
# 		Non-Null Count	
0	Туре	548 non-null	
1	URL_LENGTH	548 non-null	
2	NUMBER SPECIAL CHARACTERS		float64
3	TCP CONVERSATION EXCHANGE		
4	DIST REMOTE TCP PORT	548 non-null	
5	REMOTE IPS	548 non-null	
6	=	548 non-null	
7	APP_BYTES SOURCE APP PACKETS	548 non-null	
8	REMOTE APP PACKETS	548 non-null	
9		548 non-null	
9 10	SOURCE_APP_BYTES REMOTE APP BYTES	548 non-null	
11	APP_PACKETS	548 non-null	
12	DNS_QUERY_TIMES	548 non-null	
13	SOURCE_A	548 non-null	
14 15	SOURCE_B	548 non-null	
16	SOURCE_C SOURCE_D	548 non-null 548 non-null	float64 float64
	_		
17	SOURCE_F	548 non-null	
18	SOURCE_E	548 non-null	
19	SOURCE_G	548 non-null	
20	SOURCE_H	548 non-null	float64
21	SOURCE_I	548 non-null	
22	SOURCE_J	548 non-null	
23	SOURCE_K	548 non-null	
24	SOURCE_M	548 non-null	
25	SOURCE_L	548 non-null	float64
26	SOURCE_N	548 non-null	float64
27	SOURCE_O	548 non-null	
28	SOURCE_P	548 non-null	
29	SOURCE_R	548 non-null	
30	SOURCE_S	548 non-null	float64

dtypes: float64(30), int64(1)

memory usage: 132.8 KB

In [116]:

dataFrame.describe()

Out[116]:

	Туре	URL_LENGTH	NUMBER_SPECIAL_CHARACTERS	TCP_CONVERSATION_EX
count	548.000000	548.000000	548.000000	54
mean	0.383212	949.973475	25.015747	1
std	0.486613	3202.802599	5.605685	;
min	0.000000	10.051787	12.577687	1
25%	0.000000	15.838688	20.987638	•
50%	0.000000	18.069900	24.423510	1
75%	1.000000	23.264187	28.270650	1:
max	1.000000	12828.981333	50.880693	24

8 rows × 31 columns

In [117]:

```
dataFrame.corr()["Type"].sort_values()
```

Out[117]:

URL_LENGTH -0.228422 SOURCE I -0.138708 SOURCE_B -0.128587 SOURCE APP BYTES -0.086080 SOURCE C -0.075369 REMOTE_APP_BYTES -0.048806 SOURCE_G -0.017433 DNS_QUERY_TIMES -0.011055 SOURCE_F -0.007551 SOURCE E 0.001985 SOURCE L 0.022932 SOURCE_D 0.029479 SOURCE H 0.055045 SOURCE_O 0.063622 SOURCE_R 0.069140 SOURCE N 0.088076 APP_BYTES 0.096659 REMOTE_IPS 0.126232 SOURCE_APP_PACKETS 0.129433 REMOTE_APP_PACKETS 0.139874 SOURCE_S 0.141134 SOURCE P 0.205141 APP_PACKETS 0.240818 NUMBER_SPECIAL_CHARACTERS 0.412095 SOURCE_J 0.453197 SOURCE A 0.536539 DIST_REMOTE_TCP_PORT 0.710294 SOURCE M 0.734002 TCP_CONVERSATION_EXCHANGE 0.744570 SOURCE_K 0.784173 1.000000 Type Name: Type, dtype: float64

In [119]:

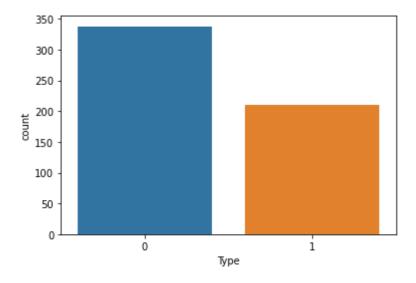
```
import matplotlib.pyplot as plt
import seaborn as sbn
```

In [120]:

sbn.countplot(x="Type",data=dataFrame)

Out[120]:

<matplotlib.axes._subplots.AxesSubplot at 0x2424f5010a0>

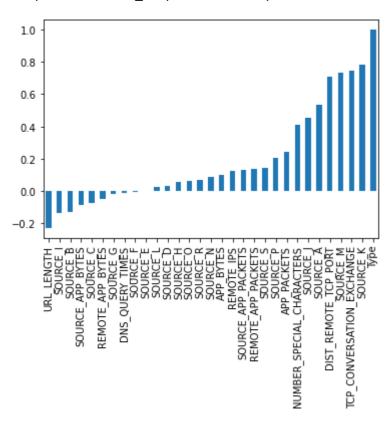


In [122]:

```
dataFrame.corr()["Type"].sort_values().plot(kind ="bar")
```

Out[122]:

<matplotlib.axes._subplots.AxesSubplot at 0x2424e28f130>



In [130]:

```
y = dataFrame["Type"].values
x = dataFrame.drop("Type",axis=1).values
```

```
In [131]:
from sklearn.model_selection import train_test_split
In [132]:
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.3,random_state=15)
In [144]:
from sklearn.preprocessing import MinMaxScaler
In [149]:
scaler = MinMaxScaler()
In [150]:
scaler.fit(x_train)
Out[150]:
MinMaxScaler()
In [151]:
x train = scaler.transform(x train)
In [153]:
x_test = scaler.transform(x_test)
In [154]:
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense ,Activation,Dropout
from tensorflow.keras.callbacks import EarlyStopping
In [155]:
x train.shape
Out[155]:
(383, 30)
In [157]:
model = Sequential()
model.add(Dense(units=30,activation ="relu")) #column sayısı kadar percetron kullanımı
 iyidir.
model.add(Dense(units=15,activation ="relu")) #bu deep network'e ilk katman ile sonkatm
an arasi percetron (30,1)
model.add(Dense(units=15,activation ="relu"))
model.add(Dense(units=1,activation ="sigmoid")) #çıkış katmanı
model.compile(loss="binary_crossentropy",optimizer = "adam")
```

In [158]:

 $model.fit(x=x_train \ ,y=y_train \ ,epochs=700 \ ,validation_data=(x_test,y_test) \ ,verbose=1)$

```
Epoch 1/700
12/12 [=============== ] - 1s 17ms/step - loss: 0.6922 - val
loss: 0.6798
Epoch 2/700
loss: 0.6704
Epoch 3/700
12/12 [=============== ] - 0s 5ms/step - loss: 0.6580 - val_
loss: 0.6580
Epoch 4/700
12/12 [============ ] - 0s 5ms/step - loss: 0.6350 - val_
loss: 0.6435
Epoch 5/700
12/12 [=========== ] - 0s 5ms/step - loss: 0.6148 - val_
loss: 0.6221
Epoch 6/700
loss: 0.5938
Epoch 7/700
loss: 0.5559
Epoch 8/700
loss: 0.5126
Epoch 9/700
loss: 0.4728
Epoch 10/700
loss: 0.4414
Epoch 11/700
loss: 0.4042
Epoch 12/700
loss: 0.3742
Epoch 13/700
loss: 0.3572
Epoch 14/700
loss: 0.3378
Epoch 15/700
loss: 0.3205
Epoch 16/700
loss: 0.3214
Epoch 17/700
loss: 0.3031
Epoch 18/700
loss: 0.2976
Epoch 19/700
loss: 0.2950
Epoch 20/700
loss: 0.2760
Epoch 21/700
```

```
loss: 0.2862
Epoch 22/700
12/12 [=========== ] - Os 5ms/step - loss: 0.1608 - val
loss: 0.2679
Epoch 23/700
loss: 0.2574
Epoch 24/700
12/12 [============= ] - 0s 5ms/step - loss: 0.1405 - val
loss: 0.2550
Epoch 25/700
loss: 0.2433
Epoch 26/700
loss: 0.2541
Epoch 27/700
loss: 0.2347
Epoch 28/700
loss: 0.2428
Epoch 29/700
loss: 0.2329
Epoch 30/700
loss: 0.2339
Epoch 31/700
loss: 0.2374
Epoch 32/700
loss: 0.2269
Epoch 33/700
loss: 0.2291
Epoch 34/700
12/12 [============== ] - Os 5ms/step - loss: 0.1141 - val
loss: 0.2210
Epoch 35/700
loss: 0.2257
Epoch 36/700
loss: 0.2153
Epoch 37/700
loss: 0.2204
Epoch 38/700
loss: 0.2125
Epoch 39/700
loss: 0.2210
Epoch 40/700
loss: 0.2082
Epoch 41/700
```

```
loss: 0.2143
Epoch 42/700
loss: 0.2050
Epoch 43/700
loss: 0.2081
Epoch 44/700
12/12 [============= ] - 0s 5ms/step - loss: 0.0981 - val
loss: 0.2066
Epoch 45/700
loss: 0.2136
Epoch 46/700
loss: 0.2115
Epoch 47/700
loss: 0.2033
Epoch 48/700
12/12 [============== ] - Os 4ms/step - loss: 0.0590 - val
loss: 0.2181
Epoch 49/700
loss: 0.2017
Epoch 50/700
loss: 0.2347
Epoch 51/700
loss: 0.2015
Epoch 52/700
loss: 0.2118
Epoch 53/700
loss: 0.2074
Epoch 54/700
loss: 0.2105
Epoch 55/700
loss: 0.2070
Epoch 56/700
12/12 [============== ] - 0s 5ms/step - loss: 0.1008 - val
loss: 0.2221
Epoch 57/700
loss: 0.2002
Epoch 58/700
loss: 0.2118
Epoch 59/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0746 - val
loss: 0.2055
Epoch 60/700
12/12 [============== ] - Os 4ms/step - loss: 0.0690 - val
loss: 0.2167
Epoch 61/700
loss: 0.2016
```

```
Epoch 62/700
12/12 [============ ] - 0s 4ms/step - loss: 0.0553 - val_
loss: 0.2198
Epoch 63/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0591 - val
loss: 0.2072
Epoch 64/700
loss: 0.2125
Epoch 65/700
loss: 0.2067
Epoch 66/700
loss: 0.2052
Epoch 67/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0670 - val_
loss: 0.2205
Epoch 68/700
loss: 0.2076
Epoch 69/700
loss: 0.2151
Epoch 70/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0507 - val_
loss: 0.2005
Epoch 71/700
loss: 0.2270
Epoch 72/700
loss: 0.1983
Epoch 73/700
12/12 [============= ] - 0s 5ms/step - loss: 0.0969 - val
loss: 0.2054
Epoch 74/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0599 - val_
loss: 0.1986
Epoch 75/700
12/12 [============== ] - Os 4ms/step - loss: 0.0620 - val
loss: 0.2019
Epoch 76/700
12/12 [============ ] - 0s 5ms/step - loss: 0.0702 - val_
loss: 0.2067
Epoch 77/700
loss: 0.1985
Epoch 78/700
loss: 0.1947
Epoch 79/700
loss: 0.2047
Epoch 80/700
loss: 0.1995
Epoch 81/700
loss: 0.2068
Epoch 82/700
```

```
loss: 0.2017
Epoch 83/700
12/12 [=========== ] - Os 6ms/step - loss: 0.0463 - val
loss: 0.2086
Epoch 84/700
loss: 0.1974
Epoch 85/700
12/12 [============= ] - 0s 5ms/step - loss: 0.0700 - val
loss: 0.2130
Epoch 86/700
loss: 0.2019
Epoch 87/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0512 - val
loss: 0.1984
Epoch 88/700
loss: 0.2041
Epoch 89/700
loss: 0.2092
Epoch 90/700
loss: 0.1947
Epoch 91/700
12/12 [============= ] - 0s 4ms/step - loss: 0.0529 - val
loss: 0.1962
Epoch 92/700
loss: 0.1934
Epoch 93/700
loss: 0.1997
Epoch 94/700
loss: 0.1871
Epoch 95/700
loss: 0.1916
Epoch 96/700
loss: 0.1928
Epoch 97/700
loss: 0.1923
Epoch 98/700
loss: 0.1861
Epoch 99/700
12/12 [============== ] - Os 4ms/step - loss: 0.0384 - val
loss: 0.1843
Epoch 100/700
loss: 0.1981
Epoch 101/700
loss: 0.1792
Epoch 102/700
```

```
loss: 0.1915
Epoch 103/700
loss: 0.1808
Epoch 104/700
loss: 0.1888
Epoch 105/700
12/12 [============== ] - Os 5ms/step - loss: 0.0492 - val
loss: 0.1879
Epoch 106/700
loss: 0.1757
Epoch 107/700
loss: 0.1813
Epoch 108/700
loss: 0.1789
Epoch 109/700
12/12 [============= ] - 0s 5ms/step - loss: 0.0238 - val
loss: 0.1804
Epoch 110/700
loss: 0.1864
Epoch 111/700
loss: 0.1749
Epoch 112/700
loss: 0.1899
Epoch 113/700
loss: 0.1852
Epoch 114/700
loss: 0.1842
Epoch 115/700
loss: 0.1751
Epoch 116/700
loss: 0.1790
Epoch 117/700
loss: 0.1777
Epoch 118/700
loss: 0.1859
Epoch 119/700
loss: 0.1708
Epoch 120/700
loss: 0.1886
Epoch 121/700
12/12 [============== ] - Os 5ms/step - loss: 0.0453 - val
loss: 0.1773
Epoch 122/700
loss: 0.1751
```

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Epoch 123/700
12/12 [============ ] - 0s 5ms/step - loss: 0.0403 - val_
loss: 0.1808
Epoch 124/700
loss: 0.1740
Epoch 125/700
loss: 0.1761
Epoch 126/700
loss: 0.1832
Epoch 127/700
loss: 0.1711
Epoch 128/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0356 - val_
loss: 0.1743
Epoch 129/700
loss: 0.1791
Epoch 130/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0374 - val
loss: 0.1869
Epoch 131/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0285 - val_
loss: 0.1707
Epoch 132/700
loss: 0.1795
Epoch 133/700
loss: 0.1716
Epoch 134/700
12/12 [============= ] - 0s 5ms/step - loss: 0.0434 - val
loss: 0.1770
Epoch 135/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0258 - val_
loss: 0.1689
Epoch 136/700
loss: 0.1662
Epoch 137/700
12/12 [============ ] - 0s 5ms/step - loss: 0.0278 - val_
loss: 0.1763
Epoch 138/700
loss: 0.1772
Epoch 139/700
loss: 0.1694
Epoch 140/700
loss: 0.1690
Epoch 141/700
loss: 0.1727
Epoch 142/700
loss: 0.1729
Epoch 143/700
```

```
loss: 0.1663
Epoch 144/700
12/12 [========== ] - Os 4ms/step - loss: 0.0260 - val
loss: 0.1757
Epoch 145/700
loss: 0.1644
Epoch 146/700
12/12 [============= ] - 0s 4ms/step - loss: 0.0216 - val
loss: 0.1723
Epoch 147/700
loss: 0.1617
Epoch 148/700
loss: 0.1582
Epoch 149/700
loss: 0.1642
Epoch 150/700
loss: 0.1670
Epoch 151/700
loss: 0.1703
Epoch 152/700
loss: 0.1561
Epoch 153/700
loss: 0.1675
Epoch 154/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0179 - val
loss: 0.1612
Epoch 155/700
loss: 0.1611
Epoch 156/700
loss: 0.1598
Epoch 157/700
loss: 0.1616
Epoch 158/700
loss: 0.1607
Epoch 159/700
loss: 0.1584
Epoch 160/700
loss: 0.1633
Epoch 161/700
loss: 0.1631
Epoch 162/700
loss: 0.1678
Epoch 163/700
```

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loss: 0.1633
Epoch 164/700
loss: 0.1666
Epoch 165/700
loss: 0.1684
Epoch 166/700
12/12 [============== ] - Os 5ms/step - loss: 0.0156 - val
loss: 0.1616
Epoch 167/700
loss: 0.1670
Epoch 168/700
loss: 0.1574
Epoch 169/700
loss: 0.1734
Epoch 170/700
12/12 [============== ] - Os 4ms/step - loss: 0.0225 - val
loss: 0.1616
Epoch 171/700
loss: 0.1744
Epoch 172/700
loss: 0.1595
Epoch 173/700
loss: 0.1669
Epoch 174/700
loss: 0.1551
Epoch 175/700
loss: 0.1761
Epoch 176/700
loss: 0.1655
Epoch 177/700
loss: 0.1676
Epoch 178/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0185 - val
loss: 0.1635
Epoch 179/700
loss: 0.1585
Epoch 180/700
loss: 0.1654
Epoch 181/700
loss: 0.1694
Epoch 182/700
12/12 [=============== ] - Os 5ms/step - loss: 0.0187 - val
loss: 0.1669
Epoch 183/700
loss: 0.1635
```

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Epoch 184/700
loss: 0.1692
Epoch 185/700
loss: 0.1653
Epoch 186/700
loss: 0.1726
Epoch 187/700
loss: 0.1656
Epoch 188/700
loss: 0.1703
Epoch 189/700
12/12 [============== ] - 0s 6ms/step - loss: 0.0116 - val_
loss: 0.1774
Epoch 190/700
loss: 0.1657
Epoch 191/700
loss: 0.1767
Epoch 192/700
12/12 [============== ] - 0s 6ms/step - loss: 0.0160 - val_
loss: 0.1705
Epoch 193/700
loss: 0.1654
Epoch 194/700
loss: 0.1612
Epoch 195/700
loss: 0.1654
Epoch 196/700
12/12 [============== ] - 0s 6ms/step - loss: 0.0142 - val_
loss: 0.1719
Epoch 197/700
loss: 0.1678
Epoch 198/700
12/12 [============ ] - 0s 6ms/step - loss: 0.0165 - val_
loss: 0.1852
Epoch 199/700
loss: 0.1644
Epoch 200/700
loss: 0.1636
Epoch 201/700
loss: 0.1694
Epoch 202/700
loss: 0.1670
Epoch 203/700
loss: 0.1929
Epoch 204/700
```

```
loss: 0.1758
Epoch 205/700
12/12 [=========== ] - Os 5ms/step - loss: 0.0150 - val
loss: 0.1750
Epoch 206/700
loss: 0.1688
Epoch 207/700
loss: 0.1652
Epoch 208/700
loss: 0.1631
Epoch 209/700
loss: 0.1702
Epoch 210/700
loss: 0.1609
Epoch 211/700
loss: 0.1621
Epoch 212/700
loss: 0.1733
Epoch 213/700
loss: 0.1592
Epoch 214/700
loss: 0.1681
Epoch 215/700
loss: 0.1587
Epoch 216/700
loss: 0.1625
Epoch 217/700
loss: 0.1551
Epoch 218/700
loss: 0.1560
Epoch 219/700
loss: 0.1576
Epoch 220/700
loss: 0.1606
Epoch 221/700
12/12 [============== ] - Os 5ms/step - loss: 0.0132 - val
loss: 0.1564
Epoch 222/700
loss: 0.1499
Epoch 223/700
loss: 0.1508
Epoch 224/700
```

```
loss: 0.1629
Epoch 225/700
loss: 0.1604
Epoch 226/700
loss: 0.1597
Epoch 227/700
12/12 [============== ] - Os 4ms/step - loss: 0.0121 - val
loss: 0.1654
Epoch 228/700
loss: 0.1650
Epoch 229/700
loss: 0.1683
Epoch 230/700
loss: 0.1669
Epoch 231/700
12/12 [============== ] - Os 4ms/step - loss: 0.0066 - val
loss: 0.1684
Epoch 232/700
loss: 0.1651
Epoch 233/700
loss: 0.1668
Epoch 234/700
loss: 0.1669
Epoch 235/700
loss: 0.1663
Epoch 236/700
loss: 0.1719
Epoch 237/700
loss: 0.1707
Epoch 238/700
loss: 0.1708
Epoch 239/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0069 - val
loss: 0.1703
Epoch 240/700
loss: 0.1685
Epoch 241/700
loss: 0.1705
Epoch 242/700
loss: 0.1785
Epoch 243/700
loss: 0.1757
Epoch 244/700
loss: 0.1716
```

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Epoch 245/700
12/12 [============ ] - 0s 4ms/step - loss: 0.0123 - val_
loss: 0.1735
Epoch 246/700
loss: 0.1797
Epoch 247/700
loss: 0.1695
Epoch 248/700
loss: 0.1738
Epoch 249/700
loss: 0.1749
Epoch 250/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0082 - val_
loss: 0.1765
Epoch 251/700
loss: 0.1769
Epoch 252/700
loss: 0.1773
Epoch 253/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0064 - val_
loss: 0.1750
Epoch 254/700
loss: 0.1768
Epoch 255/700
loss: 0.1808
Epoch 256/700
loss: 0.1817
Epoch 257/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0069 - val_
loss: 0.1804
Epoch 258/700
loss: 0.1786
Epoch 259/700
12/12 [============ ] - 0s 4ms/step - loss: 0.0059 - val_
loss: 0.1778
Epoch 260/700
loss: 0.1803
Epoch 261/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0095 - val_
loss: 0.1834
Epoch 262/700
loss: 0.1833
Epoch 263/700
loss: 0.1827
Epoch 264/700
loss: 0.1893
Epoch 265/700
```

```
loss: 0.1885
Epoch 266/700
12/12 [=========== ] - 0s 5ms/step - loss: 0.0071 - val
loss: 0.1909
Epoch 267/700
loss: 0.1889
Epoch 268/700
loss: 0.1916
Epoch 269/700
loss: 0.1902
Epoch 270/700
loss: 0.1860
Epoch 271/700
loss: 0.1890
Epoch 272/700
loss: 0.1929
Epoch 273/700
loss: 0.1948
Epoch 274/700
loss: 0.1955
Epoch 275/700
loss: 0.1958
Epoch 276/700
loss: 0.2001
Epoch 277/700
loss: 0.1990
Epoch 278/700
loss: 0.2030
Epoch 279/700
loss: 0.1980
Epoch 280/700
loss: 0.2029
Epoch 281/700
loss: 0.2008
Epoch 282/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0063 - val
loss: 0.2035
Epoch 283/700
loss: 0.2048
Epoch 284/700
loss: 0.2046
Epoch 285/700
```

```
loss: 0.2037
Epoch 286/700
loss: 0.2072
Epoch 287/700
loss: 0.2064
Epoch 288/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0064 - val
loss: 0.2069
Epoch 289/700
loss: 0.2072
Epoch 290/700
12/12 [=============== ] - 0s 4ms/step - loss: 0.0031 - val_
loss: 0.2084
Epoch 291/700
loss: 0.2121
Epoch 292/700
12/12 [============== ] - Os 4ms/step - loss: 0.0043 - val
loss: 0.2135
Epoch 293/700
loss: 0.2129
Epoch 294/700
loss: 0.2129
Epoch 295/700
loss: 0.2098
Epoch 296/700
12/12 [=============== ] - 0s 5ms/step - loss: 0.0064 - val_
loss: 0.2183
Epoch 297/700
loss: 0.2139
Epoch 298/700
loss: 0.2132
Epoch 299/700
loss: 0.2137
Epoch 300/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0044 - val
loss: 0.2131
Epoch 301/700
loss: 0.2162
Epoch 302/700
loss: 0.2193
Epoch 303/700
loss: 0.2227
Epoch 304/700
12/12 [============== ] - Os 5ms/step - loss: 0.0033 - val
loss: 0.2216
Epoch 305/700
loss: 0.2220
```

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Epoch 306/700
12/12 [============ ] - 0s 5ms/step - loss: 0.0029 - val_
loss: 0.2226
Epoch 307/700
loss: 0.2244
Epoch 308/700
loss: 0.2212
Epoch 309/700
loss: 0.2253
Epoch 310/700
loss: 0.2240
Epoch 311/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0026 - val_
loss: 0.2237
Epoch 312/700
loss: 0.2279
Epoch 313/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0054 - val
loss: 0.2307
Epoch 314/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0035 - val_
loss: 0.2310
Epoch 315/700
loss: 0.2334
Epoch 316/700
loss: 0.2317
Epoch 317/700
12/12 [============= ] - 0s 4ms/step - loss: 0.0036 - val
loss: 0.2383
Epoch 318/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0047 - val_
loss: 0.2371
Epoch 319/700
loss: 0.2360
Epoch 320/700
12/12 [============= ] - 0s 4ms/step - loss: 0.0044 - val_
loss: 0.2355
Epoch 321/700
loss: 0.2392
Epoch 322/700
loss: 0.2413
Epoch 323/700
loss: 0.2446
Epoch 324/700
loss: 0.2418
Epoch 325/700
loss: 0.2438
Epoch 326/700
```

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loss: 0.2461
Epoch 327/700
12/12 [=========== ] - 0s 5ms/step - loss: 0.0033 - val
loss: 0.2438
Epoch 328/700
loss: 0.2447
Epoch 329/700
loss: 0.2401
Epoch 330/700
loss: 0.2456
Epoch 331/700
loss: 0.2469
Epoch 332/700
loss: 0.2462
Epoch 333/700
loss: 0.2470
Epoch 334/700
loss: 0.2479
Epoch 335/700
loss: 0.2466
Epoch 336/700
loss: 0.2446
Epoch 337/700
loss: 0.2477
Epoch 338/700
loss: 0.2516
Epoch 339/700
loss: 0.2545
Epoch 340/700
loss: 0.2548
Epoch 341/700
loss: 0.2542
Epoch 342/700
loss: 0.2580
Epoch 343/700
12/12 [============== ] - Os 5ms/step - loss: 0.0027 - val
loss: 0.2582
Epoch 344/700
loss: 0.2581
Epoch 345/700
loss: 0.2599
Epoch 346/700
```

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loss: 0.2636
Epoch 347/700
loss: 0.2604
Epoch 348/700
loss: 0.2630
Epoch 349/700
12/12 [============= ] - 0s 5ms/step - loss: 0.0021 - val
loss: 0.2674
Epoch 350/700
loss: 0.2666
Epoch 351/700
loss: 0.2659
Epoch 352/700
loss: 0.2679
Epoch 353/700
12/12 [============== ] - Os 4ms/step - loss: 0.0038 - val
loss: 0.2651
Epoch 354/700
loss: 0.2676
Epoch 355/700
loss: 0.2649
Epoch 356/700
loss: 0.2698
Epoch 357/700
loss: 0.2686
Epoch 358/700
loss: 0.2747
Epoch 359/700
loss: 0.2734
Epoch 360/700
loss: 0.2726
Epoch 361/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0027 - val
loss: 0.2809
Epoch 362/700
loss: 0.2785
Epoch 363/700
loss: 0.2804
Epoch 364/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0020 - val
loss: 0.2785
Epoch 365/700
12/12 [=============== ] - Os 5ms/step - loss: 0.0020 - val
loss: 0.2815
Epoch 366/700
loss: 0.2763
```

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Epoch 367/700
12/12 [============ ] - 0s 5ms/step - loss: 0.0027 - val_
loss: 0.2816
Epoch 368/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0030 - val
loss: 0.2810
Epoch 369/700
loss: 0.2868
Epoch 370/700
loss: 0.2806
Epoch 371/700
loss: 0.2898
Epoch 372/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0017 - val_
loss: 0.2817
Epoch 373/700
loss: 0.2889
Epoch 374/700
loss: 0.2871
Epoch 375/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0015 - val_
loss: 0.2909
Epoch 376/700
loss: 0.2856
Epoch 377/700
loss: 0.2948
Epoch 378/700
12/12 [============= ] - 0s 7ms/step - loss: 0.0014 - val
loss: 0.2902
Epoch 379/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0013 - val_
loss: 0.2936
Epoch 380/700
loss: 0.2920
Epoch 381/700
12/12 [============= ] - 0s 5ms/step - loss: 0.0012 - val_
loss: 0.2963
Epoch 382/700
loss: 0.2926
Epoch 383/700
loss: 0.2937
Epoch 384/700
loss: 0.2952
Epoch 385/700
loss: 0.2978
Epoch 386/700
loss: 0.2976
Epoch 387/700
```

```
loss: 0.2994
Epoch 388/700
12/12 [=========== ] - Os 4ms/step - loss: 0.0014 - val
loss: 0.2972
Epoch 389/700
12/12 [=============== ] - 0s 5ms/step - loss: 9.4770e-04 -
val_loss: 0.3050
Epoch 390/700
loss: 0.3002
Epoch 391/700
loss: 0.3052
Epoch 392/700
loss: 0.3094
Epoch 393/700
loss: 0.3072
Epoch 394/700
12/12 [============ ] - 0s 5ms/step - loss: 9.6434e-04 -
val_loss: 0.3072
Epoch 395/700
val_loss: 0.3079
Epoch 396/700
loss: 0.3111
Epoch 397/700
loss: 0.3110
Epoch 398/700
loss: 0.3081
Epoch 399/700
12/12 [================ ] - 0s 5ms/step - loss: 9.2000e-04 -
val_loss: 0.3126
Epoch 400/700
loss: 0.3155
Epoch 401/700
loss: 0.3156
Epoch 402/700
loss: 0.3153
Epoch 403/700
loss: 0.3140
Epoch 404/700
12/12 [============== ] - Os 5ms/step - loss: 0.0012 - val
loss: 0.3151
Epoch 405/700
loss: 0.3186
Epoch 406/700
loss: 0.3195
Epoch 407/700
```

```
loss: 0.3167
Epoch 408/700
12/12 [================= ] - 0s 5ms/step - loss: 8.8994e-04 -
val loss: 0.3244
Epoch 409/700
12/12 [================= ] - Øs 5ms/step - loss: 6.4889e-04 -
val_loss: 0.3213
Epoch 410/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0012 - val
loss: 0.3227
Epoch 411/700
loss: 0.3262
Epoch 412/700
loss: 0.3278
Epoch 413/700
12/12 [================== ] - 0s 5ms/step - loss: 7.0204e-04 -
val_loss: 0.3228
Epoch 414/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0015 - val
loss: 0.3407
Epoch 415/700
loss: 0.3235
Epoch 416/700
loss: 0.3469
Epoch 417/700
loss: 0.3254
Epoch 418/700
loss: 0.3408
Epoch 419/700
12/12 [================== ] - Øs 5ms/step - loss: 9.5197e-04 -
val_loss: 0.3312
Epoch 420/700
loss: 0.3436
Epoch 421/700
12/12 [================= ] - Øs 5ms/step - loss: 6.2764e-04 -
val loss: 0.3303
Epoch 422/700
12/12 [================= ] - 0s 5ms/step - loss: 7.7290e-04 -
val loss: 0.3404
Epoch 423/700
loss: 0.3381
Epoch 424/700
loss: 0.3388
Epoch 425/700
loss: 0.3406
Epoch 426/700
12/12 [================= ] - 0s 5ms/step - loss: 9.5006e-04 -
val loss: 0.3410
Epoch 427/700
loss: 0.3448
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Epoch 428/700
loss: 0.3474
Epoch 429/700
loss: 0.3431
Epoch 430/700
loss: 0.3442
Epoch 431/700
12/12 [================ ] - Øs 5ms/step - loss: 7.5707e-04 -
val_loss: 0.3458
Epoch 432/700
12/12 [================ ] - Øs 5ms/step - loss: 8.9241e-04 -
val loss: 0.3540
Epoch 433/700
loss: 0.3407
Epoch 434/700
12/12 [================ ] - Øs 5ms/step - loss: 6.1461e-04 -
val loss: 0.3529
Epoch 435/700
loss: 0.3531
Epoch 436/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0014 - val_
loss: 0.3525
Epoch 437/700
12/12 [================== ] - Øs 5ms/step - loss: 7.9992e-04 -
val_loss: 0.3550
Epoch 438/700
12/12 [================ ] - Øs 5ms/step - loss: 7.2919e-04 -
val loss: 0.3609
Epoch 439/700
val_loss: 0.3508
Epoch 440/700
12/12 [================ ] - Øs 5ms/step - loss: 6.1434e-04 -
val_loss: 0.3637
Epoch 441/700
12/12 [================= ] - 0s 4ms/step - loss: 8.8423e-04 -
val loss: 0.3585
Epoch 442/700
12/12 [============= ] - 0s 5ms/step - loss: 9.0826e-04 -
val loss: 0.3602
Epoch 443/700
loss: 0.3584
Epoch 444/700
12/12 [================== ] - Øs 5ms/step - loss: 9.5856e-04 -
val loss: 0.3586
Epoch 445/700
12/12 [================= ] - 0s 5ms/step - loss: 8.8516e-04 -
val loss: 0.3655
Epoch 446/700
12/12 [================== ] - Øs 5ms/step - loss: 4.8013e-04 -
val loss: 0.3637
Epoch 447/700
12/12 [================= ] - 0s 4ms/step - loss: 8.0127e-04 -
val loss: 0.3616
Epoch 448/700
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loss: 0.3649
Epoch 449/700
12/12 [=============== ] - 0s 4ms/step - loss: 9.8019e-04 -
val loss: 0.3754
Epoch 450/700
12/12 [================== ] - Øs 5ms/step - loss: 7.8273e-04 -
val_loss: 0.3690
Epoch 451/700
12/12 [================ ] - 0s 4ms/step - loss: 7.9850e-04 -
val loss: 0.3765
Epoch 452/700
loss: 0.3744
Epoch 453/700
12/12 [=============== ] - 0s 4ms/step - loss: 9.6715e-04 -
val_loss: 0.3769
Epoch 454/700
12/12 [============ ] - 0s 4ms/step - loss: 8.0480e-04 -
val_loss: 0.3697
Epoch 455/700
12/12 [================ ] - 0s 4ms/step - loss: 7.2123e-04 -
val_loss: 0.3756
Epoch 456/700
12/12 [================== ] - Øs 5ms/step - loss: 7.4064e-04 -
val_loss: 0.3820
Epoch 457/700
val loss: 0.3756
Epoch 458/700
12/12 [================== ] - Øs 5ms/step - loss: 4.7437e-04 -
val_loss: 0.3822
Epoch 459/700
12/12 [=========== ] - 0s 5ms/step - loss: 9.1837e-04 -
val_loss: 0.3811
Epoch 460/700
12/12 [================ ] - 0s 4ms/step - loss: 6.0042e-04 -
val_loss: 0.3839
Epoch 461/700
12/12 [================= ] - Øs 5ms/step - loss: 7.4561e-04 -
val_loss: 0.3849
Epoch 462/700
val_loss: 0.3821
Epoch 463/700
12/12 [================= ] - 0s 5ms/step - loss: 6.3444e-04 -
val loss: 0.3857
Epoch 464/700
val_loss: 0.3913
Epoch 465/700
12/12 [================= ] - Øs 5ms/step - loss: 6.7258e-04 -
val loss: 0.3819
Epoch 466/700
12/12 [================== ] - 0s 4ms/step - loss: 9.1973e-04 -
val_loss: 0.3825
Epoch 467/700
12/12 [================ ] - 0s 5ms/step - loss: 8.2841e-04 -
val loss: 0.4034
Epoch 468/700
12/12 [================== ] - 0s 5ms/step - loss: 9.6159e-04 -
```

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val loss: 0.3808
Epoch 469/700
12/12 [============ ] - 0s 5ms/step - loss: 7.8347e-04 -
val loss: 0.3905
Epoch 470/700
12/12 [================ ] - Øs 5ms/step - loss: 7.7706e-04 -
val_loss: 0.3928
Epoch 471/700
12/12 [================ ] - 0s 5ms/step - loss: 6.7724e-04 -
val loss: 0.3938
Epoch 472/700
12/12 [================== ] - 0s 6ms/step - loss: 6.8375e-04 -
val_loss: 0.3933
Epoch 473/700
12/12 [========= ] - 0s 4ms/step - loss: 7.9729e-04 -
val loss: 0.4017
Epoch 474/700
12/12 [================== ] - 0s 5ms/step - loss: 4.0425e-04 -
val_loss: 0.3926
Epoch 475/700
12/12 [================ ] - 0s 4ms/step - loss: 6.6060e-04 -
val loss: 0.4035
Epoch 476/700
12/12 [================ ] - Øs 5ms/step - loss: 7.1002e-04 -
val_loss: 0.3960
Epoch 477/700
val_loss: 0.3990
Epoch 478/700
12/12 [============ ] - 0s 6ms/step - loss: 7.8547e-04 -
val loss: 0.4029
Epoch 479/700
val loss: 0.4019
Epoch 480/700
loss: 0.4133
Epoch 481/700
12/12 [================ ] - 0s 5ms/step - loss: 6.1710e-04 -
val loss: 0.4011
Epoch 482/700
12/12 [================= ] - Øs 5ms/step - loss: 5.6913e-04 -
val loss: 0.4115
Epoch 483/700
12/12 [================= ] - 0s 5ms/step - loss: 7.5478e-04 -
val loss: 0.4105
Epoch 484/700
12/12 [================== ] - Øs 5ms/step - loss: 6.2959e-04 -
val loss: 0.4086
Epoch 485/700
12/12 [================= ] - Øs 5ms/step - loss: 5.9612e-04 -
val loss: 0.4100
Epoch 486/700
12/12 [================= ] - 0s 6ms/step - loss: 6.1247e-04 -
val loss: 0.4163
Epoch 487/700
12/12 [================= ] - 0s 6ms/step - loss: 5.4561e-04 -
val loss: 0.4141
Epoch 488/700
12/12 [================= ] - 0s 7ms/step - loss: 4.7006e-04 -
val_loss: 0.4188
```

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Epoch 489/700
12/12 [================== ] - Øs 6ms/step - loss: 3.8527e-04 -
val loss: 0.4152
Epoch 490/700
val_loss: 0.4210
Epoch 491/700
12/12 [============ ] - 0s 5ms/step - loss: 4.6647e-04 -
val loss: 0.4120
Epoch 492/700
12/12 [================ ] - Øs 5ms/step - loss: 4.5547e-04 -
val loss: 0.4249
Epoch 493/700
12/12 [================ ] - Øs 6ms/step - loss: 4.1348e-04 -
val loss: 0.4173
Epoch 494/700
val loss: 0.4344
Epoch 495/700
12/12 [================ ] - Øs 5ms/step - loss: 8.8384e-04 -
val loss: 0.4156
Epoch 496/700
val loss: 0.4272
Epoch 497/700
12/12 [============= ] - 0s 5ms/step - loss: 6.2173e-04 -
val loss: 0.4214
Epoch 498/700
val_loss: 0.4318
Epoch 499/700
12/12 [=============== ] - Øs 6ms/step - loss: 4.9513e-04 -
val_loss: 0.4307
Epoch 500/700
val_loss: 0.4333
Epoch 501/700
12/12 [================ ] - Øs 6ms/step - loss: 7.5188e-04 -
val loss: 0.4276
Epoch 502/700
12/12 [================= ] - 0s 4ms/step - loss: 9.7065e-04 -
val loss: 0.4361
Epoch 503/700
12/12 [============ ] - 0s 5ms/step - loss: 4.9916e-04 -
val loss: 0.4313
Epoch 504/700
12/12 [================= ] - 0s 4ms/step - loss: 8.7737e-04 -
val_loss: 0.4368
Epoch 505/700
12/12 [================== ] - 0s 4ms/step - loss: 4.9786e-04 -
val loss: 0.4368
Epoch 506/700
12/12 [================= ] - 0s 5ms/step - loss: 5.8300e-04 -
val loss: 0.4408
Epoch 507/700
12/12 [================== ] - Øs 5ms/step - loss: 4.7203e-04 -
val loss: 0.4392
Epoch 508/700
12/12 [================= ] - 0s 6ms/step - loss: 5.2005e-04 -
val loss: 0.4416
Epoch 509/700
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val loss: 0.4401
Epoch 510/700
val loss: 0.4403
Epoch 511/700
12/12 [================== ] - 0s 4ms/step - loss: 3.9791e-04 -
val_loss: 0.4410
Epoch 512/700
12/12 [========= ] - 0s 5ms/step - loss: 4.9349e-04 -
val_loss: 0.4436
Epoch 513/700
val_loss: 0.4460
Epoch 514/700
val loss: 0.4410
Epoch 515/700
12/12 [============ ] - 0s 4ms/step - loss: 7.2231e-04 -
val_loss: 0.4482
Epoch 516/700
val_loss: 0.4433
Epoch 517/700
12/12 [================== ] - 0s 4ms/step - loss: 2.8740e-04 -
val_loss: 0.4517
Epoch 518/700
val loss: 0.4447
Epoch 519/700
12/12 [================== ] - Øs 6ms/step - loss: 3.7728e-04 -
val_loss: 0.4595
Epoch 520/700
12/12 [=========== ] - 0s 5ms/step - loss: 4.0757e-04 -
val_loss: 0.4466
Epoch 521/700
12/12 [================== ] - 0s 4ms/step - loss: 5.3633e-04 -
val_loss: 0.4623
Epoch 522/700
12/12 [================= ] - 0s 4ms/step - loss: 5.5107e-04 -
val loss: 0.4525
Epoch 523/700
val_loss: 0.4648
Epoch 524/700
12/12 [================= ] - Øs 5ms/step - loss: 5.5593e-04 -
val loss: 0.4558
Epoch 525/700
val_loss: 0.4614
Epoch 526/700
12/12 [================= ] - Øs 5ms/step - loss: 3.5446e-04 -
val loss: 0.4562
Epoch 527/700
12/12 [================== ] - 0s 4ms/step - loss: 4.4867e-04 -
val_loss: 0.4613
Epoch 528/700
12/12 [================= ] - 0s 4ms/step - loss: 4.6177e-04 -
val_loss: 0.4649
Epoch 529/700
12/12 [================== ] - 0s 5ms/step - loss: 5.4150e-04 -
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val loss: 0.4691
Epoch 530/700
12/12 [================ ] - 0s 6ms/step - loss: 4.3774e-04 -
val loss: 0.4564
Epoch 531/700
12/12 [================= ] - 0s 5ms/step - loss: 6.4550e-04 -
val loss: 0.4704
Epoch 532/700
val loss: 0.4652
Epoch 533/700
12/12 [============== ] - 0s 4ms/step - loss: 4.2588e-04 -
val_loss: 0.4712
Epoch 534/700
12/12 [================ ] - 0s 4ms/step - loss: 2.4392e-04 -
val loss: 0.4694
Epoch 535/700
12/12 [================== ] - 0s 4ms/step - loss: 4.7309e-04 -
val_loss: 0.4714
Epoch 536/700
val loss: 0.4731
Epoch 537/700
12/12 [================ ] - Øs 5ms/step - loss: 3.8472e-04 -
val_loss: 0.4707
Epoch 538/700
val_loss: 0.4751
Epoch 539/700
12/12 [============ ] - 0s 5ms/step - loss: 2.3994e-04 -
val loss: 0.4767
Epoch 540/700
12/12 [================ ] - 0s 4ms/step - loss: 2.8434e-04 -
val loss: 0.4768
Epoch 541/700
12/12 [================== ] - Øs 5ms/step - loss: 4.5313e-04 -
val_loss: 0.4778
Epoch 542/700
12/12 [================ ] - Øs 4ms/step - loss: 3.2429e-04 -
val loss: 0.4782
Epoch 543/700
12/12 [================= ] - 0s 4ms/step - loss: 3.3769e-04 -
val loss: 0.4807
Epoch 544/700
12/12 [================= ] - 0s 6ms/step - loss: 2.5892e-04 -
val loss: 0.4815
Epoch 545/700
12/12 [================== ] - Øs 5ms/step - loss: 5.3341e-04 -
val loss: 0.4772
Epoch 546/700
12/12 [================= ] - Øs 5ms/step - loss: 3.4615e-04 -
val loss: 0.4855
Epoch 547/700
12/12 [================= ] - Øs 5ms/step - loss: 5.3324e-04 -
val loss: 0.4809
Epoch 548/700
12/12 [================= ] - 0s 4ms/step - loss: 2.6179e-04 -
val loss: 0.4894
Epoch 549/700
val_loss: 0.4866
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Epoch 550/700
val loss: 0.4865
Epoch 551/700
12/12 [================ ] - 0s 4ms/step - loss: 3.6184e-04 -
val_loss: 0.4885
Epoch 552/700
12/12 [============ ] - 0s 4ms/step - loss: 2.7573e-04 -
val loss: 0.4892
Epoch 553/700
12/12 [================ ] - Øs 5ms/step - loss: 3.4649e-04 -
val_loss: 0.4912
Epoch 554/700
12/12 [================ ] - Øs 5ms/step - loss: 3.7890e-04 -
val loss: 0.4910
Epoch 555/700
12/12 [================ ] - Øs 5ms/step - loss: 2.7048e-04 -
val loss: 0.4940
Epoch 556/700
12/12 [================ ] - Øs 5ms/step - loss: 4.3567e-04 -
val loss: 0.4918
Epoch 557/700
val loss: 0.4919
Epoch 558/700
12/12 [============ ] - 0s 5ms/step - loss: 1.7169e-04 -
val loss: 0.4930
Epoch 559/700
val_loss: 0.5019
Epoch 560/700
12/12 [================ ] - Øs 5ms/step - loss: 2.4621e-04 -
val loss: 0.4966
Epoch 561/700
12/12 [================ ] - 0s 6ms/step - loss: 3.9557e-04 -
val_loss: 0.4965
Epoch 562/700
12/12 [================ ] - Øs 5ms/step - loss: 3.4968e-04 -
val loss: 0.4992
Epoch 563/700
12/12 [================= ] - Øs 5ms/step - loss: 2.2761e-04 -
val loss: 0.4994
Epoch 564/700
12/12 [============= ] - 0s 4ms/step - loss: 1.7879e-04 -
val loss: 0.4975
Epoch 565/700
12/12 [================= ] - 0s 4ms/step - loss: 1.9623e-04 -
val loss: 0.5036
Epoch 566/700
12/12 [================== ] - Øs 5ms/step - loss: 2.8903e-04 -
val loss: 0.5022
Epoch 567/700
12/12 [================ ] - Øs 5ms/step - loss: 3.4123e-04 -
val loss: 0.5089
Epoch 568/700
12/12 [================== ] - 0s 6ms/step - loss: 3.0401e-04 -
val loss: 0.5009
Epoch 569/700
12/12 [================ ] - 0s 4ms/step - loss: 2.4713e-04 -
val loss: 0.5058
Epoch 570/700
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val loss: 0.5016
Epoch 571/700
12/12 [========= ] - 0s 4ms/step - loss: 2.9622e-04 -
val loss: 0.5039
Epoch 572/700
12/12 [================= ] - Øs 5ms/step - loss: 1.7614e-04 -
val_loss: 0.5045
Epoch 573/700
12/12 [========= ] - 0s 5ms/step - loss: 2.2343e-04 -
val loss: 0.5092
Epoch 574/700
12/12 [================== ] - Øs 6ms/step - loss: 4.5524e-04 -
val_loss: 0.5012
Epoch 575/700
val_loss: 0.5121
Epoch 576/700
12/12 [============ ] - 0s 5ms/step - loss: 2.4129e-04 -
val_loss: 0.5121
Epoch 577/700
12/12 [================ ] - 0s 5ms/step - loss: 3.0756e-04 -
val_loss: 0.5121
Epoch 578/700
val_loss: 0.5169
Epoch 579/700
12/12 [================ ] - 0s 4ms/step - loss: 3.6483e-04 -
val loss: 0.5141
Epoch 580/700
12/12 [================== ] - 0s 4ms/step - loss: 1.9195e-04 -
val_loss: 0.5180
Epoch 581/700
12/12 [========= ] - 0s 4ms/step - loss: 2.5108e-04 -
val_loss: 0.5224
Epoch 582/700
12/12 [================= ] - 0s 5ms/step - loss: 5.8548e-04 -
val_loss: 0.5286
Epoch 583/700
loss: 0.5058
Epoch 584/700
val_loss: 0.5131
Epoch 585/700
12/12 [================= ] - 0s 5ms/step - loss: 2.6847e-04 -
val loss: 0.5103
Epoch 586/700
val_loss: 0.5178
Epoch 587/700
12/12 [================= ] - 0s 4ms/step - loss: 3.7107e-04 -
val loss: 0.5183
Epoch 588/700
12/12 [================== ] - 0s 4ms/step - loss: 3.5616e-04 -
val_loss: 0.5230
Epoch 589/700
12/12 [================ ] - 0s 5ms/step - loss: 3.1891e-04 -
val loss: 0.5232
Epoch 590/700
12/12 [================== ] - 0s 5ms/step - loss: 1.9601e-04 -
```

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val loss: 0.5293
Epoch 591/700
12/12 [================ ] - 0s 5ms/step - loss: 1.4039e-04 -
val loss: 0.5289
Epoch 592/700
val loss: 0.5304
Epoch 593/700
12/12 [========= ] - 0s 5ms/step - loss: 1.8824e-04 -
val loss: 0.5317
Epoch 594/700
12/12 [================== ] - 0s 4ms/step - loss: 1.7151e-04 -
val_loss: 0.5285
Epoch 595/700
12/12 [========== ] - 0s 5ms/step - loss: 2.3879e-04 -
val loss: 0.5308
Epoch 596/700
12/12 [================== ] - Øs 5ms/step - loss: 1.6494e-04 -
val_loss: 0.5329
Epoch 597/700
val loss: 0.5308
Epoch 598/700
12/12 [================ ] - Øs 5ms/step - loss: 2.1685e-04 -
val_loss: 0.5323
Epoch 599/700
val_loss: 0.5388
Epoch 600/700
12/12 [============ ] - 0s 4ms/step - loss: 2.3301e-04 -
val loss: 0.5345
Epoch 601/700
12/12 [================= ] - 0s 5ms/step - loss: 1.3974e-04 -
val loss: 0.5373
Epoch 602/700
12/12 [================== ] - 0s 4ms/step - loss: 1.9803e-04 -
val_loss: 0.5363
Epoch 603/700
12/12 [================ ] - Øs 5ms/step - loss: 2.1093e-04 -
val loss: 0.5351
Epoch 604/700
12/12 [================= ] - 0s 5ms/step - loss: 2.2251e-04 -
val loss: 0.5408
Epoch 605/700
12/12 [================= ] - Øs 5ms/step - loss: 1.4915e-04 -
val loss: 0.5426
Epoch 606/700
12/12 [================= ] - 0s 4ms/step - loss: 2.3692e-04 -
val loss: 0.5401
Epoch 607/700
12/12 [================= ] - 0s 5ms/step - loss: 3.1360e-04 -
val loss: 0.5417
Epoch 608/700
12/12 [================= ] - Øs 5ms/step - loss: 9.3271e-04 -
val loss: 0.5654
Epoch 609/700
12/12 [================= ] - Øs 5ms/step - loss: 4.3577e-04 -
val loss: 0.5410
Epoch 610/700
val_loss: 0.5514
```

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Epoch 611/700
12/12 [================== ] - 0s 4ms/step - loss: 2.2260e-04 -
val loss: 0.5539
Epoch 612/700
val_loss: 0.5594
Epoch 613/700
12/12 [============ ] - 0s 5ms/step - loss: 1.4592e-04 -
val loss: 0.5550
Epoch 614/700
12/12 [================ ] - 0s 5ms/step - loss: 3.0417e-04 -
val_loss: 0.5647
Epoch 615/700
12/12 [================ ] - Øs 5ms/step - loss: 1.8981e-04 -
val loss: 0.5507
Epoch 616/700
12/12 [================ ] - Øs 5ms/step - loss: 1.9410e-04 -
val loss: 0.5558
Epoch 617/700
12/12 [================ ] - 0s 5ms/step - loss: 2.0830e-04 -
val loss: 0.5563
Epoch 618/700
val_loss: 0.5566
Epoch 619/700
12/12 [============ ] - 0s 4ms/step - loss: 1.6691e-04 -
val loss: 0.5585
Epoch 620/700
val_loss: 0.5585
Epoch 621/700
12/12 [================= ] - Øs 5ms/step - loss: 1.5727e-04 -
val loss: 0.5615
Epoch 622/700
12/12 [==================== ] - 0s 4ms/step - loss: 2.3127e-04 -
val_loss: 0.5627
Epoch 623/700
12/12 [================ ] - Øs 5ms/step - loss: 2.5035e-04 -
val loss: 0.5617
Epoch 624/700
12/12 [================= ] - 0s 5ms/step - loss: 1.5310e-04 -
val loss: 0.5647
Epoch 625/700
12/12 [============= ] - 0s 5ms/step - loss: 1.6603e-04 -
val loss: 0.5622
Epoch 626/700
12/12 [================= ] - Øs 5ms/step - loss: 1.2559e-04 -
val_loss: 0.5650
Epoch 627/700
val loss: 0.5630
Epoch 628/700
12/12 [================= ] - Øs 5ms/step - loss: 2.2238e-04 -
val loss: 0.5681
Epoch 629/700
12/12 [================== ] - 0s 4ms/step - loss: 1.1848e-04 -
val loss: 0.5643
Epoch 630/700
12/12 [================== ] - Øs 5ms/step - loss: 2.2640e-04 -
val loss: 0.5718
Epoch 631/700
```

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val_loss: 0.5677
Epoch 632/700
12/12 [========= ] - 0s 4ms/step - loss: 1.7924e-04 -
val loss: 0.5738
Epoch 633/700
12/12 [================== ] - Øs 5ms/step - loss: 1.1857e-04 -
val_loss: 0.5738
Epoch 634/700
12/12 [========= ] - 0s 4ms/step - loss: 1.9561e-04 -
val_loss: 0.5714
Epoch 635/700
val_loss: 0.5743
Epoch 636/700
val_loss: 0.5747
Epoch 637/700
12/12 [============ ] - 0s 4ms/step - loss: 1.2961e-04 -
val_loss: 0.5740
Epoch 638/700
12/12 [================= ] - Øs 5ms/step - loss: 1.4557e-04 -
val_loss: 0.5780
Epoch 639/700
12/12 [================= ] - Øs 5ms/step - loss: 2.2111e-04 -
val_loss: 0.5760
Epoch 640/700
12/12 [================ ] - 0s 5ms/step - loss: 1.3728e-04 -
val loss: 0.5765
Epoch 641/700
12/12 [================== ] - Øs 5ms/step - loss: 9.8953e-05 -
val_loss: 0.5795
Epoch 642/700
12/12 [========== ] - 0s 4ms/step - loss: 2.2453e-04 -
val_loss: 0.5779
Epoch 643/700
12/12 [================== ] - 0s 4ms/step - loss: 1.6881e-04 -
val_loss: 0.5786
Epoch 644/700
12/12 [================= ] - 0s 4ms/step - loss: 1.4458e-04 -
val_loss: 0.5792
Epoch 645/700
val_loss: 0.5793
Epoch 646/700
12/12 [================= ] - 0s 5ms/step - loss: 1.1918e-04 -
val loss: 0.5843
Epoch 647/700
val_loss: 0.5818
Epoch 648/700
12/12 [================= ] - Øs 5ms/step - loss: 1.8536e-04 -
val loss: 0.5815
Epoch 649/700
12/12 [=================== ] - 0s 4ms/step - loss: 1.5640e-04 -
val_loss: 0.5800
Epoch 650/700
12/12 [================= ] - 0s 5ms/step - loss: 1.2769e-04 -
val_loss: 0.5819
Epoch 651/700
12/12 [================== ] - 0s 5ms/step - loss: 1.0314e-04 -
```

```
val_loss: 0.5815
Epoch 652/700
12/12 [================= ] - Øs 5ms/step - loss: 1.3407e-04 -
val loss: 0.5845
Epoch 653/700
12/12 [================ ] - Øs 6ms/step - loss: 1.1925e-04 -
val_loss: 0.5842
Epoch 654/700
12/12 [================ ] - 0s 4ms/step - loss: 1.8335e-04 -
val loss: 0.5829
Epoch 655/700
12/12 [================== ] - Øs 5ms/step - loss: 1.5819e-04 -
val_loss: 0.5803
Epoch 656/700
val loss: 0.5810
Epoch 657/700
12/12 [================== ] - Øs 5ms/step - loss: 1.0735e-04 -
val_loss: 0.5821
Epoch 658/700
12/12 [================ ] - 0s 4ms/step - loss: 1.2643e-04 -
val loss: 0.5802
Epoch 659/700
12/12 [================== ] - Øs 5ms/step - loss: 1.5372e-04 -
val_loss: 0.5903
Epoch 660/700
val_loss: 0.5814
Epoch 661/700
12/12 [============ ] - 0s 5ms/step - loss: 2.3418e-04 -
val loss: 0.5832
Epoch 662/700
12/12 [============ ] - 0s 4ms/step - loss: 9.6879e-05 -
val loss: 0.5858
Epoch 663/700
12/12 [================== ] - 0s 4ms/step - loss: 9.1825e-05 -
val_loss: 0.5850
Epoch 664/700
12/12 [================= ] - 0s 5ms/step - loss: 1.0235e-04 -
val_loss: 0.5860
Epoch 665/700
12/12 [================= ] - 0s 4ms/step - loss: 1.1403e-04 -
val_loss: 0.5872
Epoch 666/700
12/12 [================= ] - 0s 4ms/step - loss: 7.8325e-05 -
val loss: 0.5892
Epoch 667/700
12/12 [================== ] - Øs 5ms/step - loss: 7.6507e-05 -
val loss: 0.5883
Epoch 668/700
12/12 [================= ] - 0s 4ms/step - loss: 8.9488e-05 -
val_loss: 0.5893
Epoch 669/700
12/12 [================= ] - 0s 4ms/step - loss: 1.9305e-04 -
val_loss: 0.5913
Epoch 670/700
12/12 [================= ] - 0s 4ms/step - loss: 1.1233e-04 -
val loss: 0.5921
Epoch 671/700
val_loss: 0.5925
```

```
Epoch 672/700
12/12 [============== ] - 0s 5ms/step - loss: 7.6004e-05 -
val loss: 0.5926
Epoch 673/700
val_loss: 0.5979
Epoch 674/700
12/12 [================ ] - Øs 5ms/step - loss: 1.5673e-04 -
val loss: 0.5947
Epoch 675/700
12/12 [================ ] - 0s 5ms/step - loss: 1.0242e-04 -
val_loss: 0.5985
Epoch 676/700
12/12 [================ ] - 0s 5ms/step - loss: 7.6400e-05 -
val_loss: 0.5956
Epoch 677/700
12/12 [================ ] - Øs 4ms/step - loss: 8.6833e-05 -
val loss: 0.5931
Epoch 678/700
12/12 [================ ] - 0s 4ms/step - loss: 8.8107e-05 -
val loss: 0.5975
Epoch 679/700
val_loss: 0.5903
Epoch 680/700
12/12 [============ ] - 0s 4ms/step - loss: 9.9102e-05 -
val loss: 0.5948
Epoch 681/700
12/12 [================== ] - 0s 4ms/step - loss: 9.5769e-05 -
val_loss: 0.5941
Epoch 682/700
12/12 [============ ] - 0s 4ms/step - loss: 1.1171e-04 -
val loss: 0.5987
Epoch 683/700
12/12 [================= ] - 0s 4ms/step - loss: 7.0023e-05 -
val_loss: 0.5950
Epoch 684/700
12/12 [================ ] - Øs 5ms/step - loss: 8.6421e-05 -
val loss: 0.6030
Epoch 685/700
12/12 [================= ] - 0s 5ms/step - loss: 7.9442e-05 -
val loss: 0.5986
Epoch 686/700
12/12 [============= ] - 0s 5ms/step - loss: 7.6482e-05 -
val_loss: 0.5974
Epoch 687/700
12/12 [================= ] - 0s 4ms/step - loss: 1.1360e-04 -
val_loss: 0.6057
Epoch 688/700
12/12 [================= ] - Øs 5ms/step - loss: 8.3214e-05 -
val loss: 0.6031
Epoch 689/700
12/12 [================= ] - 0s 4ms/step - loss: 9.6466e-05 -
val loss: 0.6056
Epoch 690/700
12/12 [================== ] - 0s 4ms/step - loss: 6.8017e-05 -
val loss: 0.6039
Epoch 691/700
12/12 [================== ] - 0s 4ms/step - loss: 5.9245e-05 -
val loss: 0.6078
Epoch 692/700
```

```
12/12 [============== ] - 0s 4ms/step - loss: 7.9724e-05 -
val_loss: 0.6076
Epoch 693/700
12/12 [========== ] - 0s 4ms/step - loss: 5.8677e-05 -
val loss: 0.6087
Epoch 694/700
12/12 [============== ] - 0s 5ms/step - loss: 6.7766e-05 -
val_loss: 0.6090
Epoch 695/700
val_loss: 0.6109
Epoch 696/700
12/12 [================= ] - 0s 4ms/step - loss: 6.2186e-05 -
val_loss: 0.6118
Epoch 697/700
12/12 [================= ] - 0s 4ms/step - loss: 1.5433e-04 -
val_loss: 0.6116
Epoch 698/700
12/12 [============ ] - 0s 5ms/step - loss: 7.1333e-05 -
val_loss: 0.6142
Epoch 699/700
12/12 [================= ] - 0s 4ms/step - loss: 7.6165e-05 -
val_loss: 0.6127
Epoch 700/700
12/12 [============ ] - 0s 5ms/step - loss: 7.2566e-05 -
val_loss: 0.6155
```

Out[158]:

<tensorflow.python.keras.callbacks.History at 0x24254c4ed90>

In [159]:

model.history.history

Out[159]:

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In [160]:

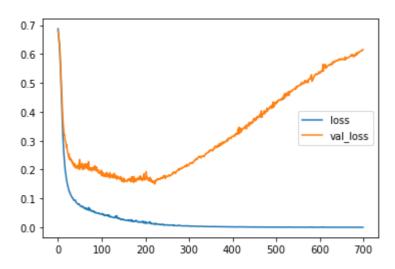
```
modelLoss = pd.DataFrame(model.history.history)
```

In [161]:

```
modelLoss.plot()
```

Out[161]:

<matplotlib.axes._subplots.AxesSubplot at 0x24252d59e20>



In [162]:

```
model = Sequential()

model.add(Dense(units=30,activation ="relu")) #column sayss kadar percetron kullanımı
iyidir.

model.add(Dense(units=15,activation ="relu")) #bu deep network'e ilk katman ile sonkatm
an arası percetron (30,1)
model.add(Dense(units=15,activation ="relu"))
model.add(Dense(units=1,activation ="sigmoid")) #çıkış katmanı

model.compile(loss="binary_crossentropy",optimizer = "adam")
```

In [164]:

```
earlyStopping = EarlyStopping(monitor = "val_loss", mode="min", verbose=1, patience=25)
```

In [165]:

 $model.fit(x = x_train , y = y_train,epochs = 700 , validation_data = (x_test,y_test) , verbose=1 , callbacks = [earlyStopping])$

```
Epoch 1/700
12/12 [=============== ] - 1s 20ms/step - loss: 0.6978 - val
loss: 0.6890
Epoch 2/700
loss: 0.6815
Epoch 3/700
12/12 [=============== ] - 0s 5ms/step - loss: 0.6725 - val_
loss: 0.6715
Epoch 4/700
12/12 [============ ] - 0s 6ms/step - loss: 0.6568 - val_
loss: 0.6557
Epoch 5/700
12/12 [=========== ] - 0s 5ms/step - loss: 0.6330 - val_
loss: 0.6327
Epoch 6/700
loss: 0.6057
Epoch 7/700
loss: 0.5663
Epoch 8/700
loss: 0.5304
Epoch 9/700
loss: 0.4990
Epoch 10/700
loss: 0.4505
Epoch 11/700
loss: 0.4213
Epoch 12/700
loss: 0.3992
Epoch 13/700
loss: 0.3754
Epoch 14/700
loss: 0.3641
Epoch 15/700
loss: 0.3442
Epoch 16/700
loss: 0.3331
Epoch 17/700
loss: 0.3289
Epoch 18/700
loss: 0.3163
Epoch 19/700
loss: 0.3048
Epoch 20/700
loss: 0.2999
Epoch 21/700
```

```
loss: 0.2837
Epoch 22/700
12/12 [============ ] - Os 5ms/step - loss: 0.1482 - val
loss: 0.3038
Epoch 23/700
loss: 0.2729
Epoch 24/700
12/12 [============= ] - 0s 5ms/step - loss: 0.1588 - val
loss: 0.3062
Epoch 25/700
loss: 0.2763
Epoch 26/700
loss: 0.2785
Epoch 27/700
loss: 0.2839
Epoch 28/700
loss: 0.2596
Epoch 29/700
loss: 0.2613
Epoch 30/700
loss: 0.2633
Epoch 31/700
loss: 0.2528
Epoch 32/700
loss: 0.2566
Epoch 33/700
loss: 0.2683
Epoch 34/700
loss: 0.2530
Epoch 35/700
loss: 0.2601
Epoch 36/700
loss: 0.2540
Epoch 37/700
loss: 0.2518
Epoch 38/700
12/12 [============== ] - Os 4ms/step - loss: 0.1065 - val
loss: 0.2612
Epoch 39/700
loss: 0.2531
Epoch 40/700
loss: 0.2632
Epoch 41/700
```

```
loss: 0.2554
Epoch 42/700
loss: 0.2582
Epoch 43/700
loss: 0.2562
Epoch 44/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0828 - val
loss: 0.2653
Epoch 45/700
loss: 0.2528
Epoch 46/700
loss: 0.2579
Epoch 47/700
loss: 0.2669
Epoch 48/700
12/12 [============= ] - Os 4ms/step - loss: 0.0633 - val
loss: 0.2554
Epoch 49/700
loss: 0.2618
Epoch 50/700
loss: 0.2607
Epoch 51/700
loss: 0.2589
Epoch 52/700
loss: 0.2600
Epoch 53/700
loss: 0.2658
Epoch 54/700
loss: 0.2625
Epoch 55/700
loss: 0.2640
Epoch 56/700
12/12 [============== ] - 0s 4ms/step - loss: 0.0510 - val
loss: 0.2647
Epoch 57/700
loss: 0.2633
Epoch 58/700
loss: 0.2649
Epoch 59/700
12/12 [============== ] - 0s 5ms/step - loss: 0.0752 - val
loss: 0.2651
Epoch 60/700
12/12 [============== ] - Os 5ms/step - loss: 0.0913 - val
loss: 0.2657
Epoch 61/700
loss: 0.2602
```

```
Epoch 62/700
```

12/12 [===========] - 0s 4ms/step - loss: 0.0527 - val_

loss: 0.2707

Epoch 00062: early stopping

Out[165]:

<tensorflow.python.keras.callbacks.History at 0x2425603d340>

In [166]:

#Erken durma oldu

In [167]:

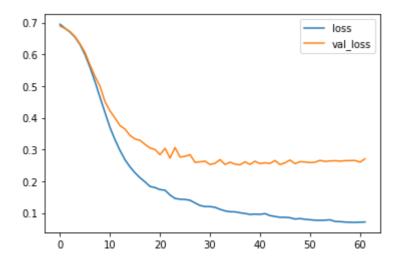
modelLoss = pd.DataFrame(model.history.history)

In [168]:

modelLoss.plot()

Out[168]:

<matplotlib.axes._subplots.AxesSubplot at 0x24256508520>



Dropout

In [169]:

```
model = Sequential()

model.add(Dense(units=30,activation ="relu")) #column sayss kadar percetron kullanımı
iyidir.
model.add(Dropout(0.6))

model.add(Dense(units=15,activation ="relu")) #bu deep network'e ilk katman ile sonkatm
an arası percetron (30,1)
model.add(Dropout(0.6))

model.add(Dense(units=15,activation ="relu"))
model.add(Dropout(0.6))

model.add(Dense(units=1,activation ="sigmoid")) #çıkış katmanı
model.compile(loss="binary_crossentropy",optimizer = "adam")
```

In [170]:

 $model.fit(x = x_train , y = y_train,epochs = 700 , validation_data = (x_test,y_test) , verbose=1 , callbacks = [earlyStopping])$

```
Epoch 1/700
loss: 0.6902
Epoch 2/700
loss: 0.6886
Epoch 3/700
12/12 [=============== ] - 0s 5ms/step - loss: 0.6807 - val_
loss: 0.6873
Epoch 4/700
loss: 0.6865
Epoch 5/700
12/12 [=========== ] - 0s 5ms/step - loss: 0.6808 - val_
loss: 0.6847
Epoch 6/700
loss: 0.6828
Epoch 7/700
loss: 0.6804
Epoch 8/700
loss: 0.6770
Epoch 9/700
loss: 0.6733
Epoch 10/700
loss: 0.6679
Epoch 11/700
loss: 0.6629
Epoch 12/700
loss: 0.6591
Epoch 13/700
loss: 0.6578
Epoch 14/700
loss: 0.6568
Epoch 15/700
loss: 0.6544
Epoch 16/700
loss: 0.6482
Epoch 17/700
12/12 [============== ] - 0s 6ms/step - loss: 0.6061 - val
loss: 0.6424
Epoch 18/700
loss: 0.6357
Epoch 19/700
loss: 0.6257
Epoch 20/700
loss: 0.6177
Epoch 21/700
```

```
loss: 0.6127
Epoch 22/700
12/12 [========== ] - Os 5ms/step - loss: 0.5927 - val
loss: 0.6037
Epoch 23/700
loss: 0.5943
Epoch 24/700
12/12 [============= ] - 0s 5ms/step - loss: 0.6033 - val
loss: 0.5852
Epoch 25/700
loss: 0.5775
Epoch 26/700
loss: 0.5661
Epoch 27/700
loss: 0.5519
Epoch 28/700
loss: 0.5327
Epoch 29/700
loss: 0.5178
Epoch 30/700
loss: 0.5129
Epoch 31/700
loss: 0.5055
Epoch 32/700
loss: 0.4950
Epoch 33/700
loss: 0.4826
Epoch 34/700
loss: 0.4679
Epoch 35/700
loss: 0.4553
Epoch 36/700
loss: 0.4445
Epoch 37/700
loss: 0.4447
Epoch 38/700
12/12 [============== ] - 0s 6ms/step - loss: 0.4469 - val
loss: 0.4372
Epoch 39/700
loss: 0.4254
Epoch 40/700
loss: 0.4177
Epoch 41/700
```

```
loss: 0.4029
Epoch 42/700
loss: 0.3904
Epoch 43/700
loss: 0.3746
Epoch 44/700
12/12 [============= ] - Os 5ms/step - loss: 0.4601 - val
loss: 0.3621
Epoch 45/700
loss: 0.3503
Epoch 46/700
12/12 [=============== ] - 0s 5ms/step - loss: 0.4101 - val_
loss: 0.3518
Epoch 47/700
loss: 0.3367
Epoch 48/700
12/12 [============== ] - Os 5ms/step - loss: 0.3891 - val
loss: 0.3230
Epoch 49/700
loss: 0.3270
Epoch 50/700
loss: 0.3289
Epoch 51/700
loss: 0.3423
Epoch 52/700
loss: 0.3187
Epoch 53/700
loss: 0.3013
Epoch 54/700
loss: 0.2967
Epoch 55/700
loss: 0.2901
Epoch 56/700
12/12 [============= ] - 0s 5ms/step - loss: 0.3538 - val
loss: 0.2892
Epoch 57/700
loss: 0.2976
Epoch 58/700
loss: 0.2983
Epoch 59/700
12/12 [============= ] - 0s 5ms/step - loss: 0.3546 - val
loss: 0.2956
Epoch 60/700
12/12 [============== ] - Os 5ms/step - loss: 0.3378 - val
loss: 0.3094
Epoch 61/700
loss: 0.2925
```

```
Epoch 62/700
12/12 [============ ] - 0s 5ms/step - loss: 0.3600 - val_
loss: 0.2851
Epoch 63/700
loss: 0.2807
Epoch 64/700
loss: 0.2790
Epoch 65/700
loss: 0.2772
Epoch 66/700
loss: 0.2689
Epoch 67/700
12/12 [=============== ] - 0s 5ms/step - loss: 0.2972 - val_
loss: 0.2627
Epoch 68/700
loss: 0.2706
Epoch 69/700
loss: 0.2778
Epoch 70/700
12/12 [============= ] - 0s 5ms/step - loss: 0.3068 - val_
loss: 0.2667
Epoch 71/700
loss: 0.2474
Epoch 72/700
loss: 0.2495
Epoch 73/700
12/12 [============= ] - 0s 5ms/step - loss: 0.3285 - val
loss: 0.2624
Epoch 74/700
12/12 [============== ] - 0s 5ms/step - loss: 0.3079 - val_
loss: 0.2647
Epoch 75/700
12/12 [============== ] - 0s 7ms/step - loss: 0.2944 - val
loss: 0.2527
Epoch 76/700
12/12 [============ ] - 0s 5ms/step - loss: 0.2893 - val_
loss: 0.2516
Epoch 77/700
loss: 0.2619
Epoch 78/700
loss: 0.2550
Epoch 79/700
loss: 0.2574
Epoch 80/700
loss: 0.2606
Epoch 81/700
loss: 0.2588
Epoch 82/700
```

```
loss: 0.2602
Epoch 83/700
12/12 [=========== ] - Os 5ms/step - loss: 0.2825 - val
loss: 0.2598
Epoch 84/700
loss: 0.2495
Epoch 85/700
12/12 [============= ] - 0s 5ms/step - loss: 0.2735 - val
loss: 0.2446
Epoch 86/700
loss: 0.2492
Epoch 87/700
loss: 0.2660
Epoch 88/700
loss: 0.2490
Epoch 89/700
loss: 0.2416
Epoch 90/700
loss: 0.2352
Epoch 91/700
loss: 0.2410
Epoch 92/700
loss: 0.2639
Epoch 93/700
loss: 0.2502
Epoch 94/700
loss: 0.2402
Epoch 95/700
loss: 0.2387
Epoch 96/700
loss: 0.2432
Epoch 97/700
loss: 0.2394
Epoch 98/700
loss: 0.2402
Epoch 99/700
12/12 [============== ] - Os 5ms/step - loss: 0.2240 - val
loss: 0.2425
Epoch 100/700
loss: 0.2475
Epoch 101/700
loss: 0.2330
Epoch 102/700
```

```
loss: 0.2398
Epoch 103/700
loss: 0.2466
Epoch 104/700
loss: 0.2521
Epoch 105/700
loss: 0.2379
Epoch 106/700
loss: 0.2311
Epoch 107/700
loss: 0.2345
Epoch 108/700
loss: 0.2361
Epoch 109/700
12/12 [============== ] - Os 4ms/step - loss: 0.2129 - val
loss: 0.2303
Epoch 110/700
loss: 0.2286
Epoch 111/700
loss: 0.2308
Epoch 112/700
loss: 0.2361
Epoch 113/700
loss: 0.2391
Epoch 114/700
loss: 0.2371
Epoch 115/700
loss: 0.2399
Epoch 116/700
loss: 0.2422
Epoch 117/700
12/12 [============== ] - 0s 6ms/step - loss: 0.1615 - val
loss: 0.2396
Epoch 118/700
loss: 0.2373
Epoch 119/700
loss: 0.2403
Epoch 120/700
12/12 [============== ] - 0s 5ms/step - loss: 0.2187 - val
loss: 0.2397
Epoch 121/700
12/12 [============== ] - Os 5ms/step - loss: 0.2002 - val
loss: 0.2376
Epoch 122/700
loss: 0.2314
```

```
Epoch 123/700
12/12 [============ ] - 0s 5ms/step - loss: 0.2461 - val_
loss: 0.2271
Epoch 124/700
12/12 [============== ] - 0s 6ms/step - loss: 0.1713 - val
loss: 0.2327
Epoch 125/700
loss: 0.2391
Epoch 126/700
loss: 0.2474
Epoch 127/700
loss: 0.2447
Epoch 128/700
12/12 [============== ] - 0s 4ms/step - loss: 0.1782 - val_
loss: 0.2437
Epoch 129/700
loss: 0.2478
Epoch 130/700
loss: 0.2517
Epoch 131/700
12/12 [============= ] - 0s 6ms/step - loss: 0.1794 - val_
loss: 0.2519
Epoch 132/700
loss: 0.2548
Epoch 133/700
loss: 0.2629
Epoch 134/700
12/12 [============= ] - 0s 5ms/step - loss: 0.2094 - val
loss: 0.2594
Epoch 135/700
12/12 [=============== ] - 0s 5ms/step - loss: 0.1777 - val_
loss: 0.2584
Epoch 136/700
loss: 0.2596
Epoch 137/700
12/12 [============= ] - 0s 5ms/step - loss: 0.2039 - val_
loss: 0.2525
Epoch 138/700
loss: 0.2468
Epoch 139/700
loss: 0.2431
Epoch 140/700
loss: 0.2442
Epoch 141/700
loss: 0.2471
Epoch 142/700
loss: 0.2461
Epoch 143/700
```

```
loss: 0.2430
Epoch 144/700
12/12 [=========== ] - Os 6ms/step - loss: 0.1693 - val
loss: 0.2477
Epoch 145/700
loss: 0.2574
Epoch 146/700
loss: 0.2608
Epoch 147/700
loss: 0.2556
Epoch 148/700
loss: 0.2569
Epoch 00148: early stopping
```

Out[170]:

<tensorflow.python.keras.callbacks.History at 0x2425657ea00>

In [171]:

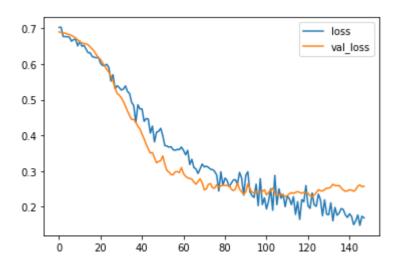
```
lossData = pd.DataFrame(model.history.history)
```

In [172]:

```
lossData.plot()
```

Out[172]:

<matplotlib.axes._subplots.AxesSubplot at 0x24257a46b80>



In [175]:

```
ourPredictions = model.predict_classes(x_test)
```

In [176]:

ourPredictions

Out[176]:

array([[0], [1], [0], [1], [0], [1], [0], [0], [1], [0], [0], [0], [0], [0], [1], [1], [0], [1], [0], [1], [1], [0], [1], [0], [1], [1], [1], [0], [0], [1], [0], [0], [1], [1], [0], [0], [1], [0], [0], [1], [1], [0], [0], [0], [0], [1], [1], [0], [1], [0], [0], [0], [0], [0], [1], [0],

[1], [0], [1],

[1],

[0],

[0],

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[1],

[1], [1], [0], [0], [0], [0], [0], [0], [0], [1], [1], [1], [1], [1], [0], [0], [0], [0], [0], [1], [0], [0], [0], [1], [1], [0], [1], [0], [0], [0], [1], [0], [1], [0], [1], [1], [1], [1], [1], [1], [1], [1], [1], [1],

In [177]:

[0]])

from sklearn.metrics import classification_report ,confusion_matrix

In [179]:

print(classification_report(y_test,ourPredictions))

	precision	recall	f1-score	support
0	0.92	0.93	0.93	91
1	0.92	0.91	0.91	74
accuracy			0.92	165
macro avg	0.92	0.92	0.92	165
weighted avg	0.92	0.92	0.92	165

In [181]:

print(confusion_matrix(y_test,ourPredictions))

[[85 6] [7 67]]

In []: