

1r3xrg4gk

August 14, 2024

0.1 Case: Build machine learning models for prediction Regression Task

0.2 Dataset: House_Price_prediction.csv

0.3 Problem Statement: Analyse the dataset and perform the steps below to build linear regression machine

learning model

0.4 Import Libraries

```
[1]: import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
%matplotlib inline
```

```
[2]: #Import Dataset
```

```
[3]: m1=pd.read_csv("House_Price_prediction.csv")
print(m1)
```

	Unnamed: 0	price	lotsize	bedrooms	bathrms	stories	garagepl	\
0	0	42000	8.674197	3	1	2	1	
1	1	38500	8.294050	2	1	1	0	
2	2	49500	8.026170	3	1	1	0	
3	3	60500	8.802372	3	1	2	0	
4	4	61000	8.757784	3	1	1	0	
..	
546	546	107500	8.699515	3	2	4	1	
547	547	108000	8.699515	3	2	3	0	
548	548	113750	8.699515	3	1	4	2	
549	549	120000	8.853665	3	1	4	2	
550	550	70000	9.464983	3	1	1	2	

	driveway_yes	recroom_yes	fullbase_yes	gashw_yes	airco_yes	\
0	1	0	1	0	0	
1	1	0	0	0	0	
2	1	0	0	0	0	

```

3          1          1          0          0          0
4          1          0          0          0          0
..          ...          ...          ...          ...          ...
546         1          0          0          0          1
547         1          0          0          0          1
548         1          1          0          0          1
549         1          0          0          0          1
550         1          0          0          0          0

```

```

      prefarea_yes
0          0
1          0
2          0
3          0
4          0
..          ...
546         0
547         0
548         0
549         0
550         0

```

[551 rows x 13 columns]

```
[4]: #Exploratory Data Analysis(EDA)
```

```
[5]: m1.head()
```

```

[5]:   Unnamed: 0  price  lotsize  bedrooms  bathrms  stories  garagepl  \
0          0  42000  8.674197          3          1          2          1
1          1  38500  8.294050          2          1          1          0
2          2  49500  8.026170          3          1          1          0
3          3  60500  8.802372          3          1          2          0
4          4  61000  8.757784          3          1          1          0

      driveway_yes  recroom_yes  fullbase_yes  gashw_yes  airco_yes  prefarea_yes
0          1          0          1          0          0          0
1          1          0          0          0          0          0
2          1          0          0          0          0          0
3          1          1          0          0          0          0
4          1          0          0          0          0          0

```

```
[6]: m1.describe()
```

```

[6]:   Unnamed: 0  price  lotsize  bedrooms  bathrms  \
count  551.000000  551.000000  551.000000  551.000000  551.000000
mean    275.000000  68445.811252    8.470413    2.967332    1.286751

```

std	159.204271	26848.486040	0.399086	0.732880	0.502165
min	0.000000	25000.000000	7.408531	1.000000	1.000000
25%	137.500000	49500.000000	8.188689	3.000000	1.000000
50%	275.000000	62500.000000	8.433812	3.000000	1.000000
75%	412.500000	82950.000000	8.757784	3.000000	2.000000
max	550.000000	190000.000000	9.692767	6.000000	4.000000

	stories	garagepl	driveway_yes	recroom_yes	fullbase_yes	\
count	551.000000	551.000000	551.000000	551.000000	551.000000	
mean	1.820327	0.698730	0.860254	0.177858	0.346642	
std	0.881334	0.863386	0.347038	0.382741	0.476333	
min	1.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	0.000000	1.000000	0.000000	0.000000	
50%	2.000000	0.000000	1.000000	0.000000	0.000000	
75%	2.000000	1.000000	1.000000	0.000000	1.000000	
max	4.000000	3.000000	1.000000	1.000000	1.000000	

	gashw_yes	airco_yes	prefarea_yes
count	551.000000	551.000000	551.000000
mean	0.045372	0.321234	0.232305
std	0.208308	0.467375	0.422686
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	0.000000	1.000000	0.000000
max	1.000000	1.000000	1.000000

```
[7]: m1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 551 entries, 0 to 550
Data columns (total 13 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Unnamed: 0      551 non-null   int64
1   price           551 non-null   int64
2   lotsize         551 non-null   float64
3   bedrooms        551 non-null   int64
4   bathrms         551 non-null   int64
5   stories         551 non-null   int64
6   garagepl        551 non-null   int64
7   driveway_yes    551 non-null   int64
8   recroom_yes     551 non-null   int64
9   fullbase_yes    551 non-null   int64
10  gashw_yes       551 non-null   int64
11  airco_yes       551 non-null   int64
12  prefarea_yes    551 non-null   int64
```

```
dtypes: float64(1), int64(12)
memory usage: 56.1 KB
```

```
[8]: print(m1.shape)
```

```
(551, 13)
```

```
[9]: m1.corr()
```

```
[9]:
```

	Unnamed: 0	price	lotsize	bedrooms	bathrms	stories	\
Unnamed: 0	1.000000	0.387924	0.386297	0.109361	0.109914	0.248420	
price	0.387924	1.000000	0.560017	0.363247	0.513014	0.435332	
lotsize	0.386297	0.560017	1.000000	0.151814	0.198791	0.112181	
bedrooms	0.109361	0.363247	0.151814	1.000000	0.371325	0.399058	
bathrms	0.109914	0.513014	0.198791	0.371325	1.000000	0.322034	
stories	0.248420	0.435332	0.112181	0.399058	0.322034	1.000000	
garagepl	0.135595	0.385734	0.365816	0.136709	0.170263	0.052983	
driveway_yes	0.315854	0.298859	0.332750	-0.010833	0.042566	0.125817	
recroom_yes	0.095841	0.253611	0.176168	0.079088	0.122017	0.046397	
fullbase_yes	-0.013450	0.175110	0.035777	0.094997	0.100567	-0.180526	
gashw_yes	-0.036458	0.089257	-0.015737	0.045456	0.066592	0.014774	
airco_yes	0.169776	0.462458	0.262216	0.158087	0.187823	0.312520	
prefarea_yes	0.503575	0.318696	0.212355	0.077366	0.062495	0.034156	

	garagepl	driveway_yes	recroom_yes	fullbase_yes	gashw_yes	\
Unnamed: 0	0.135595	0.315854	0.095841	-0.013450	-0.036458	
price	0.385734	0.298859	0.253611	0.175110	0.089257	
lotsize	0.365816	0.332750	0.176168	0.035777	-0.015737	
bedrooms	0.136709	-0.010833	0.079088	0.094997	0.045456	
bathrms	0.170263	0.042566	0.122017	0.100567	0.066592	
stories	0.052983	0.125817	0.046397	-0.180526	0.014774	
garagepl	1.000000	0.205116	0.041400	0.046609	0.066032	
driveway_yes	0.205116	1.000000	0.091646	0.040602	-0.012735	
recroom_yes	0.041400	0.091646	1.000000	0.369287	-0.010181	
fullbase_yes	0.046609	0.040602	0.369287	1.000000	0.006119	
gashw_yes	0.066032	-0.012735	-0.010181	0.006119	1.000000	
airco_yes	0.159165	0.109127	0.137408	0.037930	-0.131303	
prefarea_yes	0.087499	0.196923	0.159972	0.231448	-0.057977	

	airco_yes	prefarea_yes
Unnamed: 0	0.169776	0.503575
price	0.462458	0.318696
lotsize	0.262216	0.212355
bedrooms	0.158087	0.077366
bathrms	0.187823	0.062495
stories	0.312520	0.034156
garagepl	0.159165	0.087499

driveway_yes	0.109127	0.196923
recroom_yes	0.137408	0.159972
fullbase_yes	0.037930	0.231448
gashw_yes	-0.131303	-0.057977
airco_yes	1.000000	0.109357
prefarea_yes	0.109357	1.000000

#Splitting Data into Training and Testing Dataset

```
[10]: x=m1[['price','lotsize','bedrooms','bathrms','stories','garagepl','driveway_yes','recroom_yes']
      ↪variables
```

```
[11]: y=m1.prefarea_yes #dependant variable
```

```
[12]: from sklearn.model_selection import train_test_split
      x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=1,
      ↪)
```

```
[13]: print(x_train.shape)
      print(x_test.shape)
      print(y_train.shape)
      print(y_test.shape)
```

```
(440, 11)
(111, 11)
(440,)
(111,)
```

```
[14]: print(x_train)
      print(y_train)
```

	price	lotsize	bedrooms	bathrms	stories	garagepl	driveway_yes	\
92	163000	8.911934	4	1	2	2	1	
66	60000	8.525161	3	1	2	0	1	
201	53900	7.832014	5	2	1	1	0	
397	80750	8.803875	4	2	2	1	1	
521	105000	8.699515	4	2	4	1	1	
..		
129	127000	8.433812	3	2	2	2	1	
144	57250	8.411833	3	1	2	0	0	
72	32500	7.515345	2	1	1	0	0	
235	42500	8.378391	4	1	2	1	0	
37	67000	8.550628	3	1	4	0	1	

	recroom_yes	fullbase_yes	gashw_yes	airco_yes
92	1	1	0	1
66	0	1	0	1
201	0	1	0	1

```

397          1          1          0          0
521          1          0          0          1
..          ...          ...          ...          ...
129          1          0          0          1
144          0          1          0          1
72           0          1          0          0
235          0          0          0          0
37           0          0          0          1

```

[440 rows x 11 columns]

```

92      0
66      0
201     0
397     1
521     0
..
129     0
144     0
72      0
235     0
37      0

```

Name: prefarea_yes, Length: 440, dtype: int64

```
[15]: # Model buiding / model training
```

```

[16]: from sklearn.linear_model import LinearRegression
linreg=LinearRegression()
linreg.fit(x_train,y_train) # Model buiding / model training

#X_TRAIN =440 rows x 11 columns
#Y_TRAIN= 440 RECORDS, 1 COLUMNS

```

```
[16]: LinearRegression()
```

```
[17]: print(linreg.intercept_)
```

-0.545539630293612

```
[18]: print(linreg.coef_) # Next we try to obtain a1,a2,.....a11 and also b
```

```

[ 4.86545317e-06  5.36246111e-02  1.57066101e-03 -8.32654349e-02
 -2.47227400e-02 -3.36147082e-02  9.81946453e-02  5.34496848e-02
  1.53422486e-01 -1.91696418e-01  2.89096643e-02]

```

```

[19]: print("x_test:(price,_,
        ↳lotsize','bedrooms','bathrms','stories','garagepl','driveway_yes','recroom_yes','fullbase_y
print(x_test)

```

```
#Sales=0.0468431 X TV + 0.17854434 X Radio + 0.00258619 X Newspaper + 2.
↪9079470208164313
print("y_test: (prefarea_yes-->actual values)")
print(y_test)
```

```
x_test:(price, lotsize, 'bedrooms', 'bathrms', 'stories', 'garagepl', 'driveway_yes',
'recroom_yes', 'fullbase_yes', 'gashw_yes', 'airco_yes')
```

	price	lotsize	bedrooms	bathrms	stories	garagepl	driveway_yes \
160	63900	8.058960	3	1	2	1	1
306	67000	9.176473	4	2	2	1	1
65	60000	8.612503	3	1	2	0	1
423	62900	7.965546	3	1	2	0	1
135	90000	8.699515	4	2	4	1	1
..
408	89000	8.794825	3	2	1	0	1
17	40750	8.556414	4	1	3	0	1
247	42000	8.797095	3	1	2	0	1
124	70000	8.323608	2	1	1	1	1
257	75500	8.433812	2	2	1	2	1

	recroom_yes	fullbase_yes	gashw_yes	airco_yes
160	0	0	0	1
306	1	1	0	0
65	0	0	0	1
423	0	0	0	0
135	0	0	0	0
..
408	0	1	0	1
17	0	0	0	0
247	0	0	0	0
124	0	1	0	0
257	0	0	0	1

```
[111 rows x 11 columns]
```

```
y_test: (prefarea_yes-->actual values)
```

```
160    0
306    0
65     0
423    1
135    0
..
408    1
17     0
247    0
124    0
257    0
```

```
Name: prefarea_yes, Length: 111, dtype: int64
```

```
[20]: # Making predictions using the built model on test dataset
```

```
[21]: y_pred=linreg.predict(x_test)  #x_test-->- 111 records ,(actual values)␣  
      ↪y_test-->sales
```

```
[22]: print(y_pred)
```

```
[ 0.16301209  0.33428895  0.20733508  0.15784237  0.1643      0.38864294  
 0.3769083   0.0515332   0.22644814  0.34188307  0.0496893   0.18451213  
-0.06550692  0.2897895   0.16202616  0.04709468  0.27923778  0.22507599  
 0.12653864  0.38901906  0.21396333  0.2833614   0.22425638  0.26118611  
 0.48653114  0.22415522  0.42025623  0.66789153  0.32314802  0.23312456  
-0.09947451  0.44921925  0.24414098  0.2421242   0.14290019  0.15230468  
-0.15590387  0.02693835  0.05212203  0.39888901  0.25175938  0.17481732  
 0.3946586   -0.039609   -0.03340065 -0.010992   0.06631354  0.22592543  
 0.47371444  0.35196897  0.03637799  0.35767401  0.37024095  0.18951081  
 0.1341406   0.21810362  0.07814129  0.36179345  0.53737528  0.17067184  
 0.49532839  0.20492066  0.11088533  0.42204509 -0.02635494  0.05905336  
 0.22814137  0.12661147  0.134337   0.05050866 -0.04168664 -0.0258426  
 0.32222521  0.18876281  0.41483327  0.33644101  0.13880515 -0.00972749  
 0.17393439  0.24448947  0.0267609   0.27678444  0.07057038  0.21580421  
 0.36978681  0.29810874  0.42789253  0.29007743  0.10312811 -0.02761722  
 0.11159785  0.30699882  0.197092   -0.04589009  0.15079872  0.29827833  
 0.15449345  0.02489536  0.30511509  0.24430335  0.19575923  0.47936997  
 0.45314895  0.12874258  0.32123281  0.14540722  0.45308994  0.05860559  
 0.10074592  0.35454793  0.14582456]
```

```
[23]: print(y_test)
```

```
160    0  
306    0  
65     0  
423    1  
135    0  
..  
408    1  
17     0  
247    0  
124    0  
257    0  
Name: prefarea_yes, Length: 111, dtype: int64
```

```
[24]: from sklearn.linear_model import LinearRegression  
lr=LinearRegression()  # This is an object of the LinearRegression Class  
lr.fit(x_train,y_train) # This trains our model with the 440 training records
```

```
[24]: LinearRegression()
```



```
[25]: print(lr.intercept_)
      print(lr.coef_)
```

```
-0.545539630293612
[ 4.86545317e-06  5.36246111e-02  1.57066101e-03 -8.32654349e-02
 -2.47227400e-02 -3.36147082e-02  9.81946453e-02  5.34496848e-02
  1.53422486e-01 -1.91696418e-01  2.89096643e-02]
```

```
[26]: y_pred=lr.predict(x_test)
```

```
[27]: print(y_pred)
```

```
[ 0.16301209  0.33428895  0.20733508  0.15784237  0.1643      0.38864294
  0.3769083   0.0515332   0.22644814  0.34188307  0.0496893   0.18451213
 -0.06550692  0.2897895   0.16202616  0.04709468  0.27923778  0.22507599
  0.12653864  0.38901906  0.21396333  0.2833614   0.22425638  0.26118611
  0.48653114  0.22415522  0.42025623  0.66789153  0.32314802  0.23312456
 -0.09947451  0.44921925  0.24414098  0.2421242   0.14290019  0.15230468
 -0.15590387  0.02693835  0.05212203  0.39888901  0.25175938  0.17481732
  0.3946586   -0.039609   -0.03340065 -0.010992   0.06631354  0.22592543
  0.47371444  0.35196897  0.03637799  0.35767401  0.37024095  0.18951081
  0.1341406   0.21810362  0.07814129  0.36179345  0.53737528  0.17067184
  0.49532839  0.20492066  0.11088533  0.42204509 -0.02635494  0.05905336
  0.22814137  0.12661147  0.134337   0.05050866 -0.04168664 -0.0258426
  0.32222521  0.18876281  0.41483327  0.33644101  0.13880515 -0.00972749
  0.17393439  0.24448947  0.0267609   0.27678444  0.07057038  0.21580421
  0.36978681  0.29810874  0.42789253  0.29007743  0.10312811 -0.02761722
  0.11159785  0.30699882  0.197092   -0.04589009  0.15079872  0.29827833
  0.15449345  0.02489536  0.30511509  0.24430335  0.19575923  0.47936997
  0.45314895  0.12874258  0.32123281  0.14540722  0.45308994  0.05860559
  0.10074592  0.35454793  0.14582456]
```

```
[28]: # Next we compare our results to see how our model has performed
df=pd.DataFrame({'Actual':y_test,'Predicted':y_pred,'Difference +/-':
    ↪ y_test-y_pred})
print(df)
```

	Actual	Predicted	Difference +/-
160	0	0.163012	-0.163012
306	0	0.334289	-0.334289
65	0	0.207335	-0.207335
423	1	0.157842	0.842158
135	0	0.164300	-0.164300
..
408	1	0.453090	0.546910
17	0	0.058606	-0.058606
247	0	0.100746	-0.100746
124	0	0.354548	-0.354548

```
257         0    0.145825    -0.145825
```

```
[111 rows x 3 columns]
```

```
[29]: y_train_pred=lr.predict(x_train)
      print(y_train_pred)
```

```
[ 8.65747042e-01  3.56073886e-01  1.02014147e-01  3.81208476e-01
 3.19641148e-01  3.42863991e-01  1.15236254e-01  9.82600418e-02
 5.79238925e-02  8.65685027e-02  2.61279992e-01  2.71129466e-01
 1.23105851e-01  1.65350483e-01 -7.56530984e-02  6.97223258e-02
 2.76784436e-01  7.73194520e-02  5.57535647e-01  2.99946982e-01
 3.76226573e-01  2.27994357e-01  9.02836738e-02  4.78182688e-01
 5.96232768e-01  1.51108519e-01  7.25765979e-02  1.79387983e-02
 1.91356728e-01  1.49657903e-01  4.40436942e-01  3.17879233e-01
 1.28373746e-01  8.34867444e-02  1.91835450e-01 -7.26518143e-02
 2.87217730e-01  3.37554610e-01  9.68046337e-02  4.72558285e-02
 2.67143520e-01  2.15906004e-01 -5.29296831e-02  3.63109600e-01
 3.33272127e-01  2.30367818e-01  2.33856988e-01  3.56236912e-01
 5.50516843e-01  1.61235181e-01  1.02015921e-01  5.45812354e-01
 1.95100129e-01  7.29711075e-01  3.86136476e-01  3.62594997e-01
 4.10293929e-01  3.28149015e-01  1.44728240e-01 -2.08542858e-02
 2.55592351e-02  4.51038619e-01  3.61589328e-01  2.55175628e-01
-2.67952925e-02  1.42359723e-01  5.59405683e-01  2.82080438e-01
 3.62734142e-01  1.21783230e-01  6.49256415e-01 -4.94684300e-02
 3.52719763e-01  1.54493744e-01  7.51749029e-02  5.29385446e-02
 2.08379398e-01  3.55698526e-01  1.38226621e-02 -1.03126546e-01
 6.46230633e-02  4.22301695e-01  2.25828752e-01  1.10780756e-01
 7.77060872e-02  3.07768627e-01  1.10663357e-01  7.65683820e-02
-2.29884789e-02 -4.65102244e-02  4.83935070e-01  1.35330504e-01
 2.58802340e-01  2.56345424e-01  1.16892466e-01  2.44178513e-01
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 3.55580419e-01  4.03796546e-01  3.35418331e-01  2.03543451e-01
 2.21022892e-01  6.95945774e-02  2.19962434e-01  3.86134815e-01
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-4.50962572e-02  4.54283527e-01  2.58016446e-01  3.66388200e-01
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-4.84238160e-03  3.57918612e-01  1.61479213e-01  1.50496284e-01]
```

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1.13580856e-01	4.64207744e-01	4.71043253e-01	3.45809755e-01
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7.23847497e-02	-1.37064508e-01	2.38356247e-01	1.76541031e-01
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4.78027791e-01	2.75997465e-01	2.78595978e-01	5.14138024e-01
-1.98211339e-01	3.80066837e-01	2.35511936e-01	9.83869638e-02
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3.77060804e-01	7.19877149e-02	3.41721867e-01	5.18518078e-01
1.30980554e-01	8.33274325e-02	1.47729147e-01	5.43906805e-01
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7.62098177e-02	1.49460256e-01	1.57362309e-01	3.94516946e-01
1.42155635e-01	2.53674615e-01	2.81649770e-01	7.72724015e-01
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9.27482251e-02	2.34523906e-01	1.51512685e-01	8.85151430e-02
1.23072932e-01	2.68217448e-01	1.01925446e-01	2.33696224e-01
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3.82992780e-01	1.23490454e-01	8.08726608e-02	4.00957894e-01
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1.73316153e-01	-7.14766273e-02	3.47042479e-01	5.84499878e-01

```

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2.77931888e-01  1.72405819e-01  2.20765242e-01  6.91004879e-02
1.98149655e-01  4.50203232e-01  2.69280258e-01  4.26693000e-01
2.38422038e-01  6.41706604e-02 -4.95129018e-02  1.88629729e-01]

```

```

[30]: # Now we evaluate our model
import sklearn.metrics as metrics
print("For Testing dataset:")
print("RMSE:", np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
print('R SCORE:', metrics.r2_score(y_test, y_pred))

```

For Testing dataset:
RMSE: 0.4368626501051918
R SCORE: 0.051834588033688456

```

[31]: print("For Training dataset:")
print("RMSE:", np.sqrt(metrics.mean_squared_error(y_train, y_train_pred)))
print('R SCORE:', metrics.r2_score(y_train, y_train_pred))

```

For Training dataset:
RMSE: 0.3731035920024518
R SCORE: 0.189975119031903

```

[32]: # Model Bias is = 0.4368626501051918 - 0.3731035920024518 = 0.0637
# Model Variance is = 0.189975119031903 - 0.051834588033688456 = 0.13807
# 10% of STD = 0.1 * 26848.49 = 2684.85
# This Shows that our model has performed very well due to it's low bias and
↳ low variance.

```

0.5 .2 GRIDSEARCHCV FOR LINEAR REGRESSION

```
[33]: from sklearn.model_selection import GridSearchCV
```

```
[34]: from sklearn.preprocessing import StandardScaler
st_x= StandardScaler()
x = st_x.fit_transform(x)
```

```
[35]: parameters = {'fit_intercept':[True,False], 'positive':[True,False]}
gscv = LinearRegression()
grid = GridSearchCV(gscv, parameters, cv=5)
grid.fit(x,y)
print(grid.best_params_)
print(grid.best_estimator_)
print(grid.best_score_)
```

```
{'fit_intercept': True, 'positive': True}
LinearRegression(positive=True)
-0.463653852128387
```

0.5.1 3. BUILDING A MACHINE LEARNING MODEL FOR PREDICTING CANCER IN PATIENTS DATA SET

```
[36]: # Importing The Cancer Dataset
d2=pd.read_csv('cancer-data-2.csv')
print(d2)
```

	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	\
0	1	17.99	10.38	122.80	1001.0	
1	1	20.57	17.77	132.90	1326.0	
2	1	19.69	21.25	130.00	1203.0	
3	1	11.42	20.38	77.58	386.1	
4	1	20.29	14.34	135.10	1297.0	
..	
564	1	21.56	22.39	142.00	1479.0	
565	1	20.13	28.25	131.20	1261.0	
566	1	16.60	28.08	108.30	858.1	
567	1	20.60	29.33	140.10	1265.0	
568	0	7.76	24.54	47.92	181.0	

	smoothness_mean	compactness_mean	concavity_mean	concave	points_mean	\
0	0.11840	0.27760	0.30010		0.14710	
1	0.08474	0.07864	0.08690		0.07017	
2	0.10960	0.15990	0.19740		0.12790	
3	0.14250	0.28390	0.24140		0.10520	
4	0.10030	0.13280	0.19800		0.10430	
..	
564	0.11100	0.11590	0.24390		0.13890	

565	0.09780	0.10340	0.14400	0.09791
566	0.08455	0.10230	0.09251	0.05302
567	0.11780	0.27700	0.35140	0.15200
568	0.05263	0.04362	0.00000	0.00000

	symmetry_mean	...	radius_worst	texture_worst	perimeter_worst	\
0	0.2419	...	25.380	17.33	184.60	
1	0.1812	...	24.990	23.41	158.80	
2	0.2069	...	23.570	25.53	152.50	
3	0.2597	...	14.910	26.50	98.87	
4	0.1809	...	22.540	16.67	152.20	
..	
564	0.1726	...	25.450	26.40	166.10	
565	0.1752	...	23.690	38.25	155.00	
566	0.1590	...	18.980	34.12	126.70	
567	0.2397	...	25.740	39.42	184.60	
568	0.1587	...	9.456	30.37	59.16	

	area_worst	smoothness_worst	compactness_worst	concavity_worst	\
0	2019.0	0.16220	0.66560	0.7119	
1	1956.0	0.12380	0.18660	0.2416	
2	1709.0	0.14440	0.42450	0.4504	
3	567.7	0.20980	0.86630	0.6869	
4	1575.0	0.13740	0.20500	0.4000	
..	
564	2027.0	0.14100	0.21130	0.4107	
565	1731.0	0.11660	0.19220	0.3215	
566	1124.0	0.11390	0.30940	0.3403	
567	1821.0	0.16500	0.86810	0.9387	
568	268.6	0.08996	0.06444	0.0000	

	concave points_worst	symmetry_worst	fractal_dimension_worst
0	0.2654	0.4601	0.11890
1	0.1860	0.2750	0.08902
2	0.2430	0.3613	0.08758
3	0.2575	0.6638	0.17300
4	0.1625	0.2364	0.07678
..
564	0.2216	0.2060	0.07115
565	0.1628	0.2572	0.06637
566	0.1418	0.2218	0.07820
567	0.2650	0.4087	0.12400
568	0.0000	0.2871	0.07039

[569 rows x 31 columns]

```
[37]: d2.describe()
```

```

[37]:      diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
count  569.000000  569.000000  569.000000  569.000000  569.000000
mean    0.372583   14.127292   19.289649   91.969033  654.889104
std     0.483918    3.524049    4.301036   24.298981  351.914129
min     0.000000    6.981000    9.710000   43.790000  143.500000
25%     0.000000   11.700000   16.170000   75.170000  420.300000
50%     0.000000   13.370000   18.840000   86.240000  551.100000
75%     1.000000   15.780000   21.800000  104.100000  782.700000
max     1.000000   28.110000   39.280000  188.500000 2501.000000

      smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
count      569.000000      569.000000      569.000000      569.000000
mean         0.096360         0.104341         0.088799         0.048919
std          0.014064         0.052813         0.079720         0.038803
min          0.052630         0.019380         0.000000         0.000000
25%          0.086370         0.064920         0.029560         0.020310
50%          0.095870         0.092630         0.061540         0.033500
75%          0.105300         0.130400         0.130700         0.074000
max          0.163400         0.345400         0.426800         0.201200

      symmetry_mean  ...  radius_worst  texture_worst  perimeter_worst  \
count      569.000000  ...  569.000000      569.000000      569.000000
mean         0.181162  ...    16.269190      25.677223     107.261213
std          0.027414  ...     4.833242     6.146258     33.602542
min          0.106000  ...     7.930000     12.020000     50.410000
25%          0.161900  ...    13.010000     21.080000     84.110000
50%          0.179200  ...    14.970000     25.410000     97.660000
75%          0.195700  ...    18.790000     29.720000    125.400000
max          0.304000  ...    36.040000     49.540000    251.200000

      area_worst  smoothness_worst  compactness_worst  concavity_worst  \
count  569.000000      569.000000      569.000000      569.000000
mean   880.583128      0.132369      0.254265      0.272188
std    569.356993      0.022832      0.157336      0.208624
min    185.200000      0.071170      0.027290      0.000000
25%    515.300000      0.116600      0.147200      0.114500
50%    686.500000      0.131300      0.211900      0.226700
75%   1084.000000      0.146000      0.339100      0.382900
max   4254.000000      0.222600      1.058000      1.252000

      concave points_worst  symmetry_worst  fractal_dimension_worst
count      569.000000      569.000000      569.000000
mean         0.114606      0.290076      0.083946
std          0.065732      0.061867      0.018061
min          0.000000      0.156500      0.055040
25%          0.064930      0.250400      0.071460
50%          0.099930      0.282200      0.080040

```

75%	0.161400	0.317900	0.092080
max	0.291000	0.663800	0.207500

[8 rows x 31 columns]

[38]: d2.corr()

```
[38]:
```

	diagnosis	radius_mean	texture_mean	perimeter_mean	\
diagnosis	1.000000	0.730029	0.415185	0.742636	
radius_mean	0.730029	1.000000	0.323782	0.997855	
texture_mean	0.415185	0.323782	1.000000	0.329533	
perimeter_mean	0.742636	0.997855	0.329533	1.000000	
area_mean	0.708984	0.987357	0.321086	0.986507	
smoothness_mean	0.358560	0.170581	-0.023389	0.207278	
compactness_mean	0.596534	0.506124	0.236702	0.556936	
concavity_mean	0.696360	0.676764	0.302418	0.716136	
concave points_mean	0.776614	0.822529	0.293464	0.850977	
symmetry_mean	0.330499	0.147741	0.071401	0.183027	
fractal_dimension_mean	-0.012838	-0.311631	-0.076437	-0.261477	
radius_se	0.567134	0.679090	0.275869	0.691765	
texture_se	-0.008303	-0.097317	0.386358	-0.086761	
perimeter_se	0.556141	0.674172	0.281673	0.693135	
area_se	0.548236	0.735864	0.259845	0.744983	
smoothness_se	-0.067016	-0.222600	0.006614	-0.202694	
compactness_se	0.292999	0.206000	0.191975	0.250744	
concavity_se	0.253730	0.194204	0.143293	0.228082	
concave points_se	0.408042	0.376169	0.163851	0.407217	
symmetry_se	-0.006522	-0.104321	0.009127	-0.081629	
fractal_dimension_se	0.077972	-0.042641	0.054458	-0.005523	
radius_worst	0.776454	0.969539	0.352573	0.969476	
texture_worst	0.456903	0.297008	0.912045	0.303038	
perimeter_worst	0.782914	0.965137	0.358040	0.970387	
area_worst	0.733825	0.941082	0.343546	0.941550	
smoothness_worst	0.421465	0.119616	0.077503	0.150549	
compactness_worst	0.590998	0.413463	0.277830	0.455774	
concavity_worst	0.659610	0.526911	0.301025	0.563879	
concave points_worst	0.793566	0.744214	0.295316	0.771241	
symmetry_worst	0.416294	0.163953	0.105008	0.189115	
fractal_dimension_worst	0.323872	0.007066	0.119205	0.051019	

	area_mean	smoothness_mean	compactness_mean	\
diagnosis	0.708984	0.358560	0.596534	
radius_mean	0.987357	0.170581	0.506124	
texture_mean	0.321086	-0.023389	0.236702	
perimeter_mean	0.986507	0.207278	0.556936	
area_mean	1.000000	0.177028	0.498502	
smoothness_mean	0.177028	1.000000	0.659123	

compactness_mean	0.498502	0.659123	1.000000
concavity_mean	0.685983	0.521984	0.883121
concave points_mean	0.823269	0.553695	0.831135
symmetry_mean	0.151293	0.557775	0.602641
fractal_dimension_mean	-0.283110	0.584792	0.565369
radius_se	0.732562	0.301467	0.497473
texture_se	-0.066280	0.068406	0.046205
perimeter_se	0.726628	0.296092	0.548905
area_se	0.800086	0.246552	0.455653
smoothness_se	-0.166777	0.332375	0.135299
compactness_se	0.212583	0.318943	0.738722
concavity_se	0.207660	0.248396	0.570517
concave points_se	0.372320	0.380676	0.642262
symmetry_se	-0.072497	0.200774	0.229977
fractal_dimension_se	-0.019887	0.283607	0.507318
radius_worst	0.962746	0.213120	0.535315
texture_worst	0.287489	0.036072	0.248133
perimeter_worst	0.959120	0.238853	0.590210
area_worst	0.959213	0.206718	0.509604
smoothness_worst	0.123523	0.805324	0.565541
compactness_worst	0.390410	0.472468	0.865809
concavity_worst	0.512606	0.434926	0.816275
concave points_worst	0.722017	0.503053	0.815573
symmetry_worst	0.143570	0.394309	0.510223
fractal_dimension_worst	0.003738	0.499316	0.687382

	concavity_mean	concave points_mean	symmetry_mean	\
diagnosis	0.696360	0.776614	0.330499	
radius_mean	0.676764	0.822529	0.147741	
texture_mean	0.302418	0.293464	0.071401	
perimeter_mean	0.716136	0.850977	0.183027	
area_mean	0.685983	0.823269	0.151293	
smoothness_mean	0.521984	0.553695	0.557775	
compactness_mean	0.883121	0.831135	0.602641	
concavity_mean	1.000000	0.921391	0.500667	
concave points_mean	0.921391	1.000000	0.462497	
symmetry_mean	0.500667	0.462497	1.000000	
fractal_dimension_mean	0.336783	0.166917	0.479921	
radius_se	0.631925	0.698050	0.303379	
texture_se	0.076218	0.021480	0.128053	
perimeter_se	0.660391	0.710650	0.313893	
area_se	0.617427	0.690299	0.223970	
smoothness_se	0.098564	0.027653	0.187321	
compactness_se	0.670279	0.490424	0.421659	
concavity_se	0.691270	0.439167	0.342627	
concave points_se	0.683260	0.615634	0.393298	
symmetry_se	0.178009	0.095351	0.449137	

fractal_dimension_se	0.449301	0.257584	0.331786
radius_worst	0.688236	0.830318	0.185728
texture_worst	0.299879	0.292752	0.090651
perimeter_worst	0.729565	0.855923	0.219169
area_worst	0.675987	0.809630	0.177193
smoothness_worst	0.448822	0.452753	0.426675
compactness_worst	0.754968	0.667454	0.473200
concavity_worst	0.884103	0.752399	0.433721
concave points_worst	0.861323	0.910155	0.430297
symmetry_worst	0.409464	0.375744	0.699826
fractal_dimension_worst	0.514930	0.368661	0.438413

	...	radius_worst	texture_worst	perimeter_worst	\
diagnosis	...	0.776454	0.456903	0.782914	
radius_mean	...	0.969539	0.297008	0.965137	
texture_mean	...	0.352573	0.912045	0.358040	
perimeter_mean	...	0.969476	0.303038	0.970387	
area_mean	...	0.962746	0.287489	0.959120	
smoothness_mean	...	0.213120	0.036072	0.238853	
compactness_mean	...	0.535315	0.248133	0.590210	
concavity_mean	...	0.688236	0.299879	0.729565	
concave points_mean	...	0.830318	0.292752	0.855923	
symmetry_mean	...	0.185728	0.090651	0.219169	
fractal_dimension_mean	...	-0.253691	-0.051269	-0.205151	
radius_se	...	0.715065	0.194799	0.719684	
texture_se	...	-0.111690	0.409003	-0.102242	
perimeter_se	...	0.697201	0.200371	0.721031	
area_se	...	0.757373	0.196497	0.761213	
smoothness_se	...	-0.230691	-0.074743	-0.217304	
compactness_se	...	0.204607	0.143003	0.260516	
concavity_se	...	0.186904	0.100241	0.226680	
concave points_se	...	0.358127	0.086741	0.394999	
symmetry_se	...	-0.128121	-0.077473	-0.103753	
fractal_dimension_se	...	-0.037488	-0.003195	-0.001000	
radius_worst	...	1.000000	0.359921	0.993708	
texture_worst	...	0.359921	1.000000	0.365098	
perimeter_worst	...	0.993708	0.365098	1.000000	
area_worst	...	0.984015	0.345842	0.977578	
smoothness_worst	...	0.216574	0.225429	0.236775	
compactness_worst	...	0.475820	0.360832	0.529408	
concavity_worst	...	0.573975	0.368366	0.618344	
concave points_worst	...	0.787424	0.359755	0.816322	
symmetry_worst	...	0.243529	0.233027	0.269493	
fractal_dimension_worst	...	0.093492	0.219122	0.138957	

	area_worst	smoothness_worst	compactness_worst	\
diagnosis	0.733825	0.421465	0.590998	

radius_mean	0.941082	0.119616	0.413463
texture_mean	0.343546	0.077503	0.277830
perimeter_mean	0.941550	0.150549	0.455774
area_mean	0.959213	0.123523	0.390410
smoothness_mean	0.206718	0.805324	0.472468
compactness_mean	0.509604	0.565541	0.865809
concavity_mean	0.675987	0.448822	0.754968
concave points_mean	0.809630	0.452753	0.667454
symmetry_mean	0.177193	0.426675	0.473200
fractal_dimension_mean	-0.231854	0.504942	0.458798
radius_se	0.751548	0.141919	0.287103
texture_se	-0.083195	-0.073658	-0.092439
perimeter_se	0.730713	0.130054	0.341919
area_se	0.811408	0.125389	0.283257
smoothness_se	-0.182195	0.314457	-0.055558
compactness_se	0.199371	0.227394	0.678780
concavity_se	0.188353	0.168481	0.484858
concave points_se	0.342271	0.215351	0.452888
symmetry_se	-0.110343	-0.012662	0.060255
fractal_dimension_se	-0.022736	0.170568	0.390159
radius_worst	0.984015	0.216574	0.475820
texture_worst	0.345842	0.225429	0.360832
perimeter_worst	0.977578	0.236775	0.529408
area_worst	1.000000	0.209145	0.438296
smoothness_worst	0.209145	1.000000	0.568187
compactness_worst	0.438296	0.568187	1.000000
concavity_worst	0.543331	0.518523	0.892261
concave points_worst	0.747419	0.547691	0.801080
symmetry_worst	0.209146	0.493838	0.614441
fractal_dimension_worst	0.079647	0.617624	0.810455

	concavity_worst	concave points_worst	\
diagnosis	0.659610	0.793566	
radius_mean	0.526911	0.744214	
texture_mean	0.301025	0.295316	
perimeter_mean	0.563879	0.771241	
area_mean	0.512606	0.722017	
smoothness_mean	0.434926	0.503053	
compactness_mean	0.816275	0.815573	
concavity_mean	0.884103	0.861323	
concave points_mean	0.752399	0.910155	
symmetry_mean	0.433721	0.430297	
fractal_dimension_mean	0.346234	0.175325	
radius_se	0.380585	0.531062	
texture_se	-0.068956	-0.119638	
perimeter_se	0.418899	0.554897	
area_se	0.385100	0.538166	

smoothness_se	-0.058298	-0.102007
compactness_se	0.639147	0.483208
concavity_se	0.662564	0.440472
concave points_se	0.549592	0.602450
symmetry_se	0.037119	-0.030413
fractal_dimension_se	0.379975	0.215204
radius_worst	0.573975	0.787424
texture_worst	0.368366	0.359755
perimeter_worst	0.618344	0.816322
area_worst	0.543331	0.747419
smoothness_worst	0.518523	0.547691
compactness_worst	0.892261	0.801080
concavity_worst	1.000000	0.855434
concave points_worst	0.855434	1.000000
symmetry_worst	0.532520	0.502528
fractal_dimension_worst	0.686511	0.511114

	symmetry_worst	fractal_dimension_worst
diagnosis	0.416294	0.323872
radius_mean	0.163953	0.007066
texture_mean	0.105008	0.119205
perimeter_mean	0.189115	0.051019
area_mean	0.143570	0.003738
smoothness_mean	0.394309	0.499316
compactness_mean	0.510223	0.687382
concavity_mean	0.409464	0.514930
concave points_mean	0.375744	0.368661
symmetry_mean	0.699826	0.438413
fractal_dimension_mean	0.334019	0.767297
radius_se	0.094543	0.049559
texture_se	-0.128215	-0.045655
perimeter_se	0.109930	0.085433
area_se	0.074126	0.017539
smoothness_se	-0.107342	0.101480
compactness_se	0.277878	0.590973
concavity_se	0.197788	0.439329
concave points_se	0.143116	0.310655
symmetry_se	0.389402	0.078079
fractal_dimension_se	0.111094	0.591328
radius_worst	0.243529	0.093492
texture_worst	0.233027	0.219122
perimeter_worst	0.269493	0.138957
area_worst	0.209146	0.079647
smoothness_worst	0.493838	0.617624
compactness_worst	0.614441	0.810455
concavity_worst	0.532520	0.686511
concave points_worst	0.502528	0.511114

symmetry_worst	1.000000	0.537848
fractal_dimension_worst	0.537848	1.000000

[31 rows x 31 columns]

```
[39]: # Indicate the dependent(x) and independent(y) variables
x=d2.iloc[:,1:]
y=d2.iloc[:,0]
```

```
[40]: # Verify x and y
print(x)
print(y)
```

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	\
0	17.99	10.38	122.80	1001.0	0.11840	
1	20.57	17.77	132.90	1326.0	0.08474	
2	19.69	21.25	130.00	1203.0	0.10960	
3	11.42	20.38	77.58	386.1	0.14250	
4	20.29	14.34	135.10	1297.0	0.10030	
..	
564	21.56	22.39	142.00	1479.0	0.11100	
565	20.13	28.25	131.20	1261.0	0.09780	
566	16.60	28.08	108.30	858.1	0.08455	
567	20.60	29.33	140.10	1265.0	0.11780	
568	7.76	24.54	47.92	181.0	0.05263	

	compactness_mean	concavity_mean	concave	points_mean	symmetry_mean	\
0	0.27760	0.30010		0.14710	0.2419	
1	0.07864	0.08690		0.07017	0.1812	
2	0.15990	0.19740		0.12790	0.2069	
3	0.28390	0.24140		0.10520	0.2597	
4	0.13280	0.19800		0.10430	0.1809	
..	
564	0.11590	0.24390		0.13890	0.1726	
565	0.10340	0.14400		0.09791	0.1752	
566	0.10230	0.09251		0.05302	0.1590	
567	0.27700	0.35140		0.15200	0.2397	
568	0.04362	0.00000		0.00000	0.1587	

	fractal_dimension_mean	...	radius_worst	texture_worst	\
0	0.07871	...	25.380	17.33	
1	0.05667	...	24.990	23.41	
2	0.05999	...	23.570	25.53	
3	0.09744	...	14.910	26.50	
4	0.05883	...	22.540	16.67	
..	
564	0.05623	...	25.450	26.40	

565	0.05533	...	23.690	38.25
566	0.05648	...	18.980	34.12
567	0.07016	...	25.740	39.42
568	0.05884	...	9.456	30.37

	perimeter_worst	area_worst	smoothness_worst	compactness_worst	\
0	184.60	2019.0	0.16220	0.66560	
1	158.80	1956.0	0.12380	0.18660	
2	152.50	1709.0	0.14440	0.42450	
3	98.87	567.7	0.20980	0.86630	
4	152.20	1575.0	0.13740	0.20500	
..	
564	166.10	2027.0	0.14100	0.21130	
565	155.00	1731.0	0.11660	0.19220	
566	126.70	1124.0	0.11390	0.30940	
567	184.60	1821.0	0.16500	0.86810	
568	59.16	268.6	0.08996	0.06444	

	concavity_worst	concave points_worst	symmetry_worst	\
0	0.7119	0.2654	0.4601	
1	0.2416	0.1860	0.2750	
2	0.4504	0.2430	0.3613	
3	0.6869	0.2575	0.6638	
4	0.4000	0.1625	0.2364	
..	
564	0.4107	0.2216	0.2060	
565	0.3215	0.1628	0.2572	
566	0.3403	0.1418	0.2218	
567	0.9387	0.2650	0.4087	
568	0.0000	0.0000	0.2871	

	fractal_dimension_worst
0	0.11890
1	0.08902
2	0.08758
3	0.17300
4	0.07678
..	...
564	0.07115
565	0.06637
566	0.07820
567	0.12400
568	0.07039

[569 rows x 30 columns]

0	1
1	1
2	1

```

3      1
4      1
..
564    1
565    1
566    1
567    1
568    0
Name: diagnosis, Length: 569, dtype: int64

```

```

[41]: #split the dataset into training and testing datasets
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.1,random_state=2)

```

```

[42]: # displaying the training datasets
print('X TRAIN:\n',x_train)
print('\nY TRAIN:\n',y_train)

```

```

X TRAIN:
      radius_mean  texture_mean  perimeter_mean  area_mean  smoothness_mean  \
60             10.17         14.88           64.55       311.9           0.11340
3              11.42         20.38           77.58       386.1           0.14250
426            10.48         14.98           67.49       333.6           0.09816
204            12.47         18.60           81.09       481.9           0.09965
430            14.90         22.53          102.10       685.0           0.09947
..            ...           ...           ...           ...           ...
299            10.51         23.09           66.85       334.2           0.10150
534            10.96         17.62           70.79       365.6           0.09687
493            12.46         12.83           78.83       477.3           0.07372
527            12.34         12.27           78.94       468.5           0.09003
168            17.47         24.68          116.10       984.6           0.10490

      compactness_mean  concavity_mean  concave points_mean  symmetry_mean  \
60             0.08061         0.010840           0.01290           0.2743
3              0.28390         0.241400           0.10520           0.2597
426            0.10130         0.063350           0.02218           0.1925
204            0.10580         0.080050           0.03821           0.1925
430            0.22250         0.273300           0.09711           0.2041
..            ...           ...           ...           ...
299            0.06797         0.024950           0.01875           0.1695
534            0.09752         0.052630           0.02788           0.1619
493            0.04043         0.007173           0.01149           0.1613
527            0.06307         0.029580           0.02647           0.1689
168            0.16030         0.215900           0.10430           0.1538

      fractal_dimension_mean  ...  radius_worst  texture_worst  \
60             0.06960  ...           11.02           17.45
3              0.09744  ...           14.91           26.50

```

426	0.06915	...	12.13	21.57
204	0.06373	...	14.97	24.64
430	0.06898	...	16.35	27.57
..
299	0.06556	...	10.93	24.22
534	0.06408	...	11.62	26.51
493	0.06013	...	13.19	16.36
527	0.05808	...	13.61	19.27
168	0.06365	...	23.14	32.33

	perimeter_worst	area_worst	smoothness_worst	compactness_worst	\
60	69.86	368.6	0.12750	0.09866	
3	98.87	567.7	0.20980	0.86630	
426	81.41	440.4	0.13270	0.29960	
204	96.05	677.9	0.14260	0.23780	
430	125.40	832.7	0.14190	0.70900	
..	
299	70.10	362.7	0.11430	0.08614	
534	76.43	407.5	0.14280	0.25100	
493	83.24	534.0	0.09439	0.06477	
527	87.22	564.9	0.12920	0.20740	
168	155.30	1660.0	0.13760	0.38300	

	concavity_worst	concave points_worst	symmetry_worst	\
60	0.02168	0.02579	0.3557	
3	0.68690	0.25750	0.6638	
426	0.29390	0.09310	0.3020	
204	0.26710	0.10150	0.3014	
430	0.90190	0.24750	0.2866	
..	
299	0.04158	0.03125	0.2227	
534	0.21230	0.09861	0.2289	
493	0.01674	0.02680	0.2280	
527	0.17910	0.10700	0.3110	
168	0.48900	0.17210	0.2160	

	fractal_dimension_worst
60	0.08020
3	0.17300
426	0.09646
204	0.08750
430	0.11550
..	...
299	0.06777
534	0.08278
493	0.07028
527	0.07592
168	0.09300

[512 rows x 30 columns]

Y TRAIN:

```
60      0
3       1
426     0
204     0
430     1
..
299     0
534     0
493     0
527     0
168     1
```

Name: diagnosis, Length: 512, dtype: int64

```
[43]: #datasets shape
print('X:\n',x_train.shape)
print('Y:\n',y_train.shape)
```

X:

(512, 30)

Y:

(512,)

```
[44]: # Display testing datasets
print('X:\n',x_test)
print('Y:\n',y_test)
```

X:

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	\
528	13.940	13.17	90.31	594.2	0.12480	
291	14.960	19.10	97.03	687.3	0.08992	
467	9.668	18.10	61.06	286.3	0.08311	
108	22.270	19.67	152.80	1509.0	0.13260	
340	14.420	16.54	94.15	641.2	0.09751	
256	19.550	28.77	133.60	1207.0	0.09260	
160	11.750	20.18	76.10	419.8	0.10890	
306	13.200	15.82	84.07	537.3	0.08511	
155	12.250	17.94	78.27	460.3	0.08654	
511	14.810	14.70	94.66	680.7	0.08472	
171	13.430	19.63	85.84	565.4	0.09048	
109	11.340	21.26	72.48	396.5	0.08759	
275	11.890	17.36	76.20	435.6	0.12250	
200	12.230	19.56	78.54	461.0	0.09586	
55	11.520	18.75	73.34	409.0	0.09524	
161	19.190	15.94	126.30	1157.0	0.08694	

67	11.310	19.04	71.80	394.1	0.08139
540	11.540	14.44	74.65	402.9	0.09984
281	11.740	14.02	74.24	427.3	0.07813
72	17.200	24.52	114.20	929.4	0.10710
152	9.731	15.34	63.78	300.2	0.10720
304	11.460	18.16	73.59	403.1	0.08853
246	13.200	17.43	84.13	541.6	0.07215
294	12.720	13.78	81.78	492.1	0.09667
453	14.530	13.98	93.86	644.2	0.10990
517	19.890	20.26	130.50	1214.0	0.10370
544	13.870	20.70	89.77	584.8	0.09578
500	15.040	16.74	98.73	689.4	0.09883
1	20.570	17.77	132.90	1326.0	0.08474
365	20.440	21.78	133.80	1293.0	0.09150
209	15.270	12.91	98.17	725.5	0.08182
84	12.000	15.65	76.95	443.3	0.09723
312	12.760	13.37	82.29	504.1	0.08794
265	20.730	31.12	135.70	1419.0	0.09469
129	19.790	25.12	130.40	1192.0	0.10150
355	12.560	19.07	81.92	485.8	0.08760
178	13.010	22.22	82.01	526.4	0.06251
40	13.440	21.58	86.18	563.0	0.08162
303	10.490	18.61	66.86	334.3	0.10680
103	9.876	19.40	63.95	298.3	0.10050
567	20.600	29.33	140.10	1265.0	0.11780
141	16.110	18.05	105.10	813.0	0.09721
561	11.200	29.37	70.67	386.0	0.07449
320	10.250	16.18	66.52	324.2	0.10610
512	13.400	20.52	88.64	556.7	0.11060
463	11.600	18.36	73.88	412.7	0.08508
525	8.571	13.10	54.53	221.3	0.10360
332	11.220	19.86	71.94	387.3	0.10540
368	21.710	17.25	140.90	1546.0	0.09384
516	18.310	20.58	120.80	1052.0	0.10680
371	15.190	13.21	97.65	711.8	0.07963
444	18.030	16.85	117.50	990.0	0.08947
363	16.500	18.29	106.60	838.1	0.09686
251	11.500	18.45	73.28	407.4	0.09345
222	10.180	17.53	65.12	313.1	0.10610
205	15.120	16.68	98.78	716.6	0.08876
136	11.710	16.67	74.72	423.6	0.10510

	compactness_mean	concavity_mean	concave points_mean	symmetry_mean \
528	0.09755	0.101000	0.066150	0.1976
291	0.09823	0.059400	0.048190	0.1879
467	0.05428	0.014790	0.005769	0.1680
108	0.27680	0.426400	0.182300	0.2556
340	0.11390	0.080070	0.042230	0.1912

256	0.20630	0.178400	0.114400	0.1893
160	0.11410	0.068430	0.037380	0.1993
306	0.05251	0.001461	0.003261	0.1632
155	0.06679	0.038850	0.023310	0.1970
511	0.05016	0.034160	0.025410	0.1659
171	0.06288	0.058580	0.034380	0.1598
109	0.06575	0.051330	0.018990	0.1487
275	0.07210	0.059290	0.074040	0.2015
200	0.08087	0.041870	0.041070	0.1979
55	0.05473	0.030360	0.022780	0.1920
161	0.11850	0.119300	0.096670	0.1741
67	0.04701	0.037090	0.022300	0.1516
540	0.11200	0.067370	0.025940	0.1818
281	0.04340	0.022450	0.027630	0.2101
72	0.18300	0.169200	0.079440	0.1927
152	0.15990	0.410800	0.078570	0.2548
304	0.07694	0.033440	0.015020	0.1411
246	0.04524	0.043360	0.011050	0.1487
294	0.08393	0.012880	0.019240	0.1638
453	0.09242	0.068950	0.064950	0.1650
517	0.13100	0.141100	0.094310	0.1802
544	0.10180	0.036880	0.023690	0.1620
500	0.13640	0.077210	0.061420	0.1668
1	0.07864	0.086900	0.070170	0.1812
365	0.11310	0.097990	0.077850	0.1618
209	0.06230	0.058920	0.031570	0.1359
84	0.07165	0.041510	0.018630	0.2079
312	0.07948	0.040520	0.025480	0.1601
265	0.11430	0.136700	0.086460	0.1769
129	0.15890	0.254500	0.114900	0.2202
355	0.10380	0.103000	0.043910	0.1533
178	0.01938	0.001595	0.001852	0.1395
40	0.06031	0.031100	0.020310	0.1784
303	0.06678	0.022970	0.017800	0.1482
103	0.09697	0.061540	0.030290	0.1945
567	0.27700	0.351400	0.152000	0.2397
141	0.11370	0.094470	0.059430	0.1861
561	0.03558	0.000000	0.000000	0.1060
320	0.11110	0.067260	0.039650	0.1743
512	0.14690	0.144500	0.081720	0.2116
463	0.05855	0.033670	0.017770	0.1516
525	0.07632	0.025650	0.015100	0.1678
332	0.06779	0.005006	0.007583	0.1940
368	0.08562	0.116800	0.084650	0.1717
516	0.12480	0.156900	0.094510	0.1860
371	0.06934	0.033930	0.026570	0.1721
444	0.12320	0.109000	0.062540	0.1720
363	0.08468	0.058620	0.048350	0.1495

251	0.05991	0.026380	0.020690	0.1834
222	0.08502	0.017680	0.019150	0.1910
205	0.09588	0.075500	0.040790	0.1594
136	0.06095	0.035920	0.026000	0.1339

	fractal_dimension_mean	...	radius_worst	texture_worst	\
528	0.06457	...	14.620	15.38	
291	0.05852	...	16.250	26.19	
467	0.06412	...	11.150	24.62	
108	0.07039	...	28.400	28.01	
340	0.06412	...	16.670	21.51	
256	0.06232	...	25.050	36.27	
160	0.06453	...	13.320	26.21	
306	0.05894	...	14.410	20.45	
155	0.06228	...	13.590	25.22	
511	0.05348	...	15.610	17.58	
171	0.05671	...	17.980	29.87	
109	0.06529	...	13.010	29.15	
275	0.05875	...	12.400	18.99	
200	0.06013	...	14.440	28.36	
55	0.05907	...	12.840	22.47	
161	0.05176	...	22.030	17.81	
67	0.05667	...	12.330	23.84	
540	0.06782	...	12.260	19.68	
281	0.06113	...	13.310	18.26	
72	0.06487	...	23.320	33.82	
152	0.09296	...	11.020	19.49	
304	0.06243	...	12.680	21.61	
246	0.05635	...	13.940	27.82	
294	0.06100	...	13.500	17.48	
453	0.06121	...	15.800	16.93	
517	0.06188	...	23.730	25.23	
544	0.06688	...	15.050	24.75	
500	0.06869	...	16.760	20.43	
1	0.05667	...	24.990	23.41	
365	0.05557	...	24.310	26.37	
209	0.05526	...	17.380	15.92	
84	0.05968	...	13.670	24.90	
312	0.06140	...	14.190	16.40	
265	0.05674	...	32.490	47.16	
129	0.06113	...	22.630	33.58	
355	0.06184	...	13.370	22.43	
178	0.05234	...	14.000	29.02	
40	0.05587	...	15.930	30.25	
303	0.06600	...	11.060	24.54	
103	0.06322	...	10.760	26.83	
567	0.07016	...	25.740	39.42	
141	0.06248	...	19.920	25.27	

561	0.05502	...	11.920	38.30
320	0.07279	...	11.280	20.61
512	0.07325	...	16.410	29.66
463	0.05859	...	12.770	24.02
525	0.07126	...	9.473	18.45
332	0.06028	...	11.980	25.78
368	0.05054	...	30.750	26.44
516	0.05941	...	21.860	26.20
371	0.05544	...	16.200	15.73
444	0.05780	...	20.380	22.02
363	0.05593	...	18.130	25.45
251	0.05934	...	12.970	22.46
222	0.06908	...	11.170	22.84
205	0.05986	...	17.770	20.24
136	0.05945	...	13.330	25.48

	perimeter_worst	area_worst	smoothness_worst	compactness_worst	\
528	94.52	653.3	0.13940	0.13640	
291	109.10	809.8	0.13130	0.30300	
467	71.11	380.2	0.13880	0.12550	
108	206.80	2360.0	0.17010	0.69970	
340	111.40	862.1	0.12940	0.33710	
256	178.60	1926.0	0.12810	0.53290	
160	88.91	543.9	0.13580	0.18920	
306	92.00	636.9	0.11280	0.13460	
155	86.60	564.2	0.12170	0.17880	
511	101.70	760.2	0.11390	0.10110	
171	116.60	993.6	0.14010	0.15460	
109	83.99	518.1	0.16990	0.21960	
275	79.46	472.4	0.13590	0.08368	
200	92.15	638.4	0.14290	0.20420	
55	81.81	506.2	0.12490	0.08720	
161	146.60	1495.0	0.11240	0.20160	
67	78.00	466.7	0.12900	0.09148	
540	78.78	457.8	0.13450	0.21180	
281	84.70	533.7	0.10360	0.08500	
72	151.60	1681.0	0.15850	0.73940	
152	71.04	380.5	0.12920	0.27720	
304	82.69	489.8	0.11440	0.17890	
246	88.28	602.0	0.11010	0.15080	
294	88.54	553.7	0.12980	0.14720	
453	103.10	749.9	0.13470	0.14780	
517	160.50	1646.0	0.14170	0.33090	
544	99.17	688.6	0.12640	0.20370	
500	109.70	856.9	0.11350	0.21760	
1	158.80	1956.0	0.12380	0.18660	
365	161.20	1780.0	0.13270	0.23760	
209	113.70	932.7	0.12220	0.21860	

84	87.78	567.9	0.13770	0.20030
312	92.04	618.8	0.11940	0.22080
265	214.00	3432.0	0.14010	0.26440
129	148.70	1589.0	0.12750	0.38610
355	89.02	547.4	0.10960	0.20020
178	88.18	608.8	0.08125	0.03432
40	102.50	787.9	0.10940	0.20430
303	70.76	375.4	0.14130	0.10440
103	72.22	361.2	0.15590	0.23020
567	184.60	1821.0	0.16500	0.86810
141	129.00	1233.0	0.13140	0.22360
561	75.19	439.6	0.09267	0.05494
320	71.53	390.4	0.14020	0.23600
512	113.30	844.4	0.15740	0.38560
463	82.68	495.1	0.13420	0.18080
525	63.30	275.6	0.16410	0.22350
332	76.91	436.1	0.14240	0.09669
368	199.50	3143.0	0.13630	0.16280
516	142.20	1493.0	0.14920	0.25360
371	104.50	819.1	0.11260	0.17370
444	133.30	1292.0	0.12630	0.26660
363	117.20	1009.0	0.13380	0.16790
251	83.12	508.9	0.11830	0.10490
222	71.94	375.6	0.14060	0.14400
205	117.70	989.5	0.14910	0.33310
136	86.16	546.7	0.12710	0.10280

	concavity_worst	concave points_worst	symmetry_worst	\
528	0.155900	0.101500	0.2160	
291	0.180400	0.148900	0.2962	
467	0.064090	0.025000	0.3057	
108	0.960800	0.291000	0.4055	
340	0.375500	0.141400	0.3053	
256	0.425100	0.194100	0.2818	
160	0.195600	0.079090	0.3168	
306	0.011200	0.025000	0.2651	
155	0.194300	0.082110	0.3113	
511	0.110100	0.079550	0.2334	
171	0.264400	0.116000	0.2884	
109	0.312000	0.082780	0.2829	
275	0.071530	0.089460	0.2220	
200	0.137700	0.108000	0.2668	
55	0.090760	0.063160	0.3306	
161	0.226400	0.177700	0.2443	
67	0.144400	0.069610	0.2400	
540	0.179700	0.069180	0.2329	
281	0.067350	0.082900	0.3101	
72	0.656600	0.189900	0.3313	

152	0.821600	0.157100	0.3108
304	0.122600	0.055090	0.2208
246	0.229800	0.049700	0.2767
294	0.052330	0.063430	0.2369
453	0.137300	0.106900	0.2606
517	0.418500	0.161300	0.2549
544	0.137700	0.068450	0.2249
500	0.185600	0.101800	0.2177
1	0.241600	0.186000	0.2750
365	0.270200	0.176500	0.2609
209	0.296200	0.103500	0.2320
84	0.226700	0.076320	0.3379
312	0.176900	0.084110	0.2564
265	0.344200	0.165900	0.2868
129	0.567300	0.173200	0.3305
355	0.238800	0.092650	0.2121
178	0.007977	0.009259	0.2295
40	0.208500	0.111200	0.2994
303	0.084230	0.065280	0.2213
103	0.264400	0.097490	0.2622
567	0.938700	0.265000	0.4087
141	0.280200	0.121600	0.2792
561	0.000000	0.000000	0.1566
320	0.189800	0.097440	0.2608
512	0.510600	0.205100	0.3585
463	0.186000	0.082880	0.3210
525	0.175400	0.085120	0.2983
332	0.013350	0.020220	0.3292
368	0.286100	0.182000	0.2510
516	0.375900	0.151000	0.3074
371	0.136200	0.081780	0.2487
444	0.429000	0.153500	0.2842
363	0.166300	0.091230	0.2394
251	0.081050	0.065440	0.2740
222	0.065720	0.055750	0.3055
205	0.332700	0.125200	0.3415
136	0.104600	0.069680	0.1712

	fractal_dimension_worst
528	0.07253
291	0.08472
467	0.07875
108	0.09789
340	0.08764
256	0.10050
160	0.07987
306	0.08385
155	0.08132

511	0.06142
171	0.07371
109	0.08832
275	0.06033
200	0.08174
55	0.07036
161	0.06251
67	0.06641
540	0.08134
281	0.06688
72	0.13390
152	0.12590
304	0.07638
246	0.07198
294	0.06922
453	0.07810
517	0.09136
544	0.08492
500	0.08549
1	0.08902
365	0.06735
209	0.07474
84	0.07924
312	0.08253
265	0.08218
129	0.08465
355	0.07188
178	0.05843
40	0.07146
303	0.07842
103	0.08490
567	0.12400
141	0.08158
561	0.05905
320	0.09702
512	0.11090
463	0.07863
525	0.10490
332	0.06522
368	0.06494
516	0.07863
371	0.06766
444	0.08225
363	0.06469
251	0.06487
222	0.08797
205	0.09740
136	0.07343

[57 rows x 30 columns]

Y:

528	0
291	0
467	0
108	1
340	0
256	1
160	0
306	0
155	0
511	0
171	1
109	0
275	0
200	0
55	0
161	1
67	0
540	0
281	0
72	1
152	0
304	0
246	0
294	0
453	0
517	1
544	0
500	0
1	1
365	1
209	0
84	0
312	0
265	1
129	1
355	0
178	0
40	1
303	0
103	0
567	1
141	1
561	0
320	0
512	1

```

463    0
525    0
332    0
368    1
516    1
371    0
444    1
363    0
251    0
222    0
205    1
136    0
Name: diagnosis, dtype: int64

```

```

[45]: #scaling our data
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler() # Object of StandardScaler Class
x_train_scaled=scaler.fit_transform(x_train)
x_test_scaled=scaler.transform(x_test)

```

```

[46]: # Now we train our model to learn the datasets
from sklearn.linear_model import LogisticRegression
lgr=LogisticRegression()
lgr.fit(x_train_scaled,y_train) # Model is trained with the 512 training records

```

```

[46]: LogisticRegression()

```

```

[47]: # Then we test our model
y_pred=lgr.predict(x_test_scaled)
print( y_pred)

```

```

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

```

```

[48]: # We compare the Actual value to the predicted values
dfm=pd.DataFrame({'Actual':y_test, 'Predicted':y_pred, 'Difference':
    ↪y_test-y_pred})
print(dfm)

```

	Actual	Predicted	Difference
528	0	0	0
291	0	0	0
467	0	0	0
108	1	1	0
340	0	0	0
256	1	1	0
160	0	0	0
306	0	0	0

155	0	0	0
511	0	0	0
171	1	1	0
109	0	0	0
275	0	0	0
200	0	0	0
55	0	0	0
161	1	1	0
67	0	0	0
540	0	0	0
281	0	0	0
72	1	1	0
152	0	0	0
304	0	0	0
246	0	0	0
294	0	0	0
453	0	0	0
517	1	1	0
544	0	0	0
500	0	0	0
1	1	1	0
365	1	1	0
209	0	0	0
84	0	0	0
312	0	0	0
265	1	1	0
129	1	1	0
355	0	0	0
178	0	0	0
40	1	0	1
303	0	0	0
103	0	0	0
567	1	1	0
141	1	1	0
561	0	0	0
320	0	0	0
512	1	1	0
463	0	0	0
525	0	0	0
332	0	0	0
368	1	1	0
516	1	1	0
371	0	0	0
444	1	1	0
363	0	1	-1
251	0	0	0
222	0	0	0
205	1	1	0

136 0 0 0

```
[49]: # Observating the differences where the data is not zero, the prediction was
      ↪WRONG
      # Therefore our prediction looks near accurate
```

```
[50]: # our regression equation we looks like
      print(lgr.intercept_) # Gives the value of 'b'
      print(lgr.coef_)     # Gives the 30 coefficients of the regression equation
```

```
[-0.15791469]
[[ 0.51563131  0.35322049  0.48347474  0.56198034  0.2312156 -0.59345537
   0.79362221  1.04598705 -0.15160525 -0.28608271  1.22193988 -0.05599549
   0.68455271  0.94413944  0.21225854 -0.7550556 -0.09215395  0.40112978
  -0.18033158 -0.67414476  0.98243049  1.2028827  0.83067229  0.97306258
   0.86102185  0.00832564  0.81321907  0.79232381  0.81335579  0.53795661]]
```

```
[51]: # Next we evaluate our model
      from sklearn.metrics import classification_report
      from sklearn.metrics import confusion_matrix
      cf=confusion_matrix(y_test,y_pred)
      print(cf)
      print("Classification Report For Testing Dataset:")
      print(classification_report(y_test,y_pred))
```

```
[[38  1]
 [ 1 17]]
```

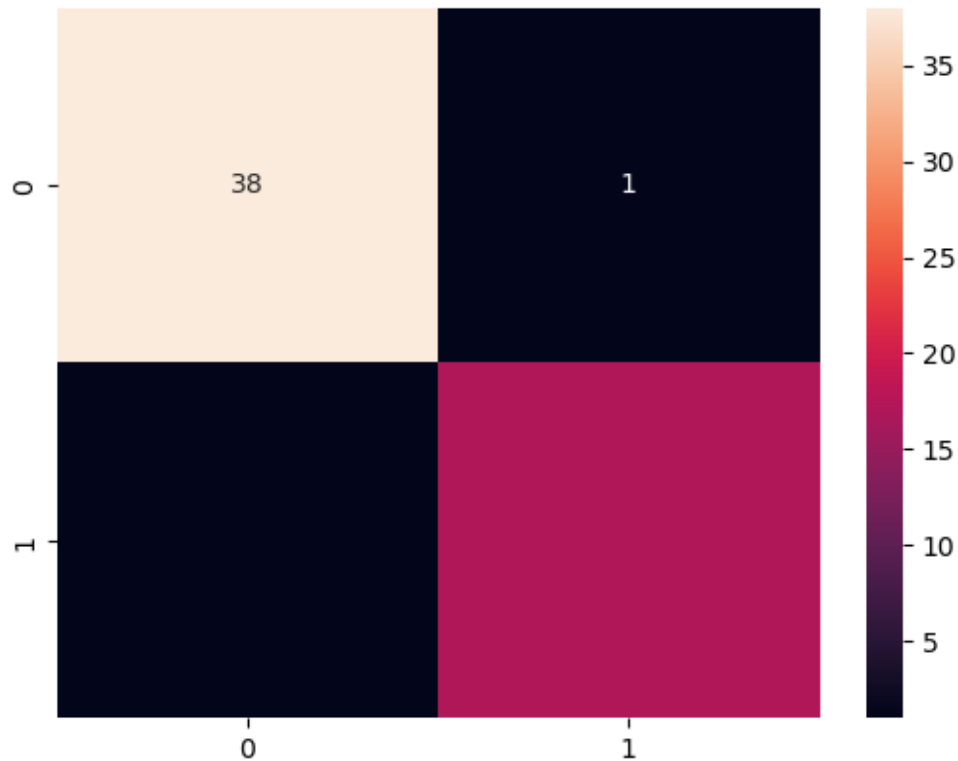
Classification Report For Testing Dataset:

	precision	recall	f1-score	support
0	0.97	0.97	0.97	39
1	0.94	0.94	0.94	18
accuracy			0.96	57
macro avg	0.96	0.96	0.96	57
weighted avg	0.96	0.96	0.96	57

```
[52]: # the Model Accuracy is = 96%
      # our model has learn the dataset (precision, recall and f1 score are constant
      ↪for both +ve and -ve predictions)
```

```
[53]: # Heatmap
      cf=confusion_matrix(y_test,y_pred)
      sns.heatmap(cf,annot=True)
```

```
[53]: <Axes: >
```



0.6 4. USING THE K-NN ON CLASSIFICATION MODEL

```
[54]: # Scaling The Dataset
from sklearn.preprocessing import StandardScaler
st_x= StandardScaler()
x= st_x.fit_transform(x)
```

```
[55]: #importing liabery
from sklearn.neighbors import KNeighborsRegressor
```

```
[56]: #Tuning The Parameters
parameters = {'n_neighbors': range(30),
              'metric':['manhattan','euclidean']}
c = KNeighborsRegressor()
grid = GridSearchCV(c, parameters, cv=5)
grid.fit(x,y)
print("Best Parameters:",grid.best_params_)
print("Best Estimators:",grid.best_estimator_)
print("Best Score:",grid.best_score_)
```

Best Parameters: {'metric': 'manhattan', 'n_neighbors': 2}

Best Estimators: KNeighborsRegressor(metric='manhattan', n_neighbors=2)

Best Score: 0.8688563481494486

```
C:\Users\PC\anaconda3\Lib\site-
packages\sklearn\model_selection\_validation.py:378: FitFailedWarning:
10 fits failed out of a total of 300.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.
```

Below are more details about the failures:

```
-----
10 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\PC\anaconda3\Lib\site-
packages\sklearn\model_selection\_validation.py", line 686, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\Users\PC\anaconda3\Lib\site-
packages\sklearn\neighbors\_regression.py", line 215, in fit
    self._validate_params()
  File "C:\Users\PC\anaconda3\Lib\site-packages\sklearn\base.py", line 600, in
_validate_params
    validate_parameter_constraints(
  File "C:\Users\PC\anaconda3\Lib\site-
packages\sklearn\utils\_param_validation.py", line 97, in
validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'n_neighbors'
parameter of KNeighborsRegressor must be an int in the range [1, inf) or None.
Got 0 instead.
```

```
warnings.warn(some_fits_failed_message, FitFailedWarning)
C:\Users\PC\anaconda3\Lib\site-packages\sklearn\model_selection\_search.py:952:
UserWarning: One or more of the test scores are non-finite: [      nan
0.77474909 0.86885635 0.86803264 0.8579427  0.8601354
0.86278342 0.86005462 0.85770716 0.85638616 0.85895758 0.85783803
0.85087744 0.84624967 0.84450975 0.84081186 0.84011566 0.84033493
0.83749609 0.83508343 0.83336695 0.83088478 0.82958427 0.82858995
0.82593815 0.82496799 0.82279226 0.82224485 0.82259019 0.82008483
      nan 0.80155327 0.82798541 0.85156749 0.85649723 0.8598864
0.85453138 0.85033685 0.85028413 0.84813779 0.84795082 0.8446083
0.84186243 0.84597571 0.84221027 0.83891439 0.83474065 0.8337275
0.83258391 0.82925887 0.82954448 0.82847209 0.82732878 0.82646872
0.82522312 0.82591248 0.82418473 0.82014577 0.82088392 0.81866076]
warnings.warn(
```

```
[ ]: # the Best Estimators was accurate in this case too.
```