```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
data=pd.read csv("data 2.csv")
data.info()
    <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 569 entries, 0 to 568
     Data columns (total 33 columns):
         Column
                                  Non-Null Count Dtype
      0
         id
                                  569 non-null
                                                  int64
         diagnosis
                                  569 non-null
      1
                                                  object
         radius mean
                                  569 non-null
                                                  float64
      3
         texture mean
                                  569 non-null
                                                  float64
                                  569 non-null
         perimeter mean
                                                  float64
      5
                                  569 non-null
                                                  float64
          area mean
         smoothness mean
                                  569 non-null
                                                  float64
         compactness mean
                                  569 non-null
                                                  float64
         concavity mean
                                  569 non-null
                                                  float64
                                                  float64
         concave points mean
                                  569 non-null
      10 symmetry mean
                                  569 non-null
                                                  float64
      11 fractal dimension mean
                                  569 non-null
                                                  float64
      12 radius se
                                  569 non-null
                                                  float64
                                                  float64
      13 texture se
                                  569 non-null
      14 perimeter se
                                  569 non-null
                                                  float64
                                                  float64
      15 area_se
                                  569 non-null
      16 smoothness se
                                  569 non-null
                                                  float64
      17 compactness se
                                  569 non-null
                                                  float64
      18 concavity_se
```

569 non-null

float64

19	concave points_se	569 non-null	float64
20	symmetry_se	569 non-null	float64
21	<pre>fractal_dimension_se</pre>	569 non-null	float64
22	radius_worst	569 non-null	float64
23	texture_worst	569 non-null	float64
24	perimeter_worst	569 non-null	float64
25	area_worst	569 non-null	float64
26	smoothness_worst	569 non-null	float64
27	compactness_worst	569 non-null	float64
28	concavity_worst	569 non-null	float64
29	concave points_worst	569 non-null	float64
30	symmetry_worst	569 non-null	float64
31	<pre>fractal_dimension_worst</pre>	569 non-null	float64
32	Unnamed: 32	0 non-null	float64

dtypes: float64(31), int64(1), object(1)

memory usage: 146.8+ KB

data.shape

(569, 33)

data.head()

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean
0	842302	М	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001
1	842517	М	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869
2	84300903	М	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974
3	84348301	М	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414
4	84358402	М	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980

#data cleaning
data=pd.DataFrame(data)

data2=data.drop(columns= ['id','diagnosis','Unnamed: 32'])

data2

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavit <sub>!</sub>
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	О
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	О
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	О
3	11.42	20.38	77.58	386.1	0.14250	0.28390	О
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	О
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	О
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	О
566	16.60	28.08	108.30	858.1	0.08455	0.10230	О
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	О
568	7.76	24.54	47.92	181.0	0.05263	0.04362	О

569 rows × 30 columns

disease\_type=data['diagnosis'].astype('category')

disease\_type

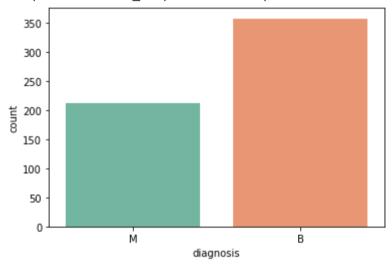
- 0 M
- 1 M
- 2 M
- 3 M

```
4 M
...
564 M
565 M
566 M
567 M
568 B
Name: diagnosis, Length: 569, dtype
```

Name: diagnosis, Length: 569, dtype: category Categories (2, object): ['B', 'M']

sns.countplot(x='diagnosis',data=data,palette='Set2')

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f49cc808810>



target=disease\_type.replace(('M','B'),(1,0))
target

```
565
            1
     566
            1
     567
            1
     568
     Name: diagnosis, Length: 569, dtype: int64
from sklearn.model selection import train test split
x train,x test,y train,y test = train test split(data2,target,test size =0.3)
print(x train.shape)
print(x test.shape)
print(y train.shape)
print(y test.shape)
     (398, 30)
     (171, 30)
     (398,)
     (171,)
#applying the Logistic Regression
from sklearn.linear model import LogisticRegression
classifier=LogisticRegression()
classifier.fit(x train,y train)
lr pridict = classifier.predict(x test)
import sklearn.metrics
from sklearn.metrics import classification report, accuracy score
prediction=classifier.predict(x_test)
prediction
print(classification_report(y_test, prediction))
                   precision
                                recall f1-score
                                                 support
```

```
0.95
                             0.95
                                                  109
           0
                                       0.95
                   0.92
                             0.90
                                       0.91
           1
                                                   62
                                       0.94
                                                  171
    accuracy
  macro avg
                   0.93
                             0.93
                                       0.93
                                                  171
weighted avg
                   0.94
                             0.94
                                       0.94
                                                  171
```

```
#Decision Tree
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
dtree = DecisionTreeClassifier()
dtree.fit(x_train,y_train)
y_pred_train = dtree.predict(x_train)
y_pred_test = dtree.predict(x_test)

print("Bias = Accuracy", accuracy_score(y_train,y_pred_train))
print("Variance = Accuracy", accuracy_score(y_test,y_pred_test))

Bias = Accuracy 1.0
    Variance = Accuracy 0.9005847953216374

tree.plot_tree(dtree.fit(data2,target))
```

```
[\text{Text}(209.25, 203.85, 'X[20] <= 16.795 \setminus i = 0.468 \setminus samples = 569 \setminus i = [357, 212]'),
  Text(136.01250000000000, 176.67000000000000, 'X[27] \le 0.136 \ngini = 0.159\nsamples = 379\nvalue = [34]
   Text(78.46875, 149.49, 'X[10] <= 1.048\ngini = 0.03\nsamples = 333\nvalue = [328, 5]'),
  Text(68.00625000000001, 122.31, 'X[13] \le 38.605 \text{ lngini} = 0.024 \text{ lnsamples} = 332 \text{ lnvalue} = [328, 4]'),
   Text(41.85, 95.13, X[14] <= 0.003 \text{ ngini} = 0.012 \text{ nsamples} = 319 \text{ nvalue} = [317, 2]'),
   Text(20.925, 67.9499999999999, 'X[19] <= 0.001\ngini = 0.245\nsamples = 7\nvalue = [6, 1]'),
   Text(10.4625, 40.770000000000001, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
  Text(31.387500000000003, 40.77000000000001, 'gini = 0.0\nsamples = 6\nvalue = [6, 0]'),
   Text(62.77500000000006, 67.949999999999, 'X[21] <= 33.27\ngini = 0.006\nsamples = 312\nvalue = [311
   Text(52.3125, 40.77000000000001, 'gini = 0.0\nsamples = 292\nvalue = [292, 0]'),
   Text(73.2375, 40.77000000000001, X[21] \le 33.56 \cdot 10^{-2} = 0.095 \cdot 10^{-2} = 20 \cdot 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10^{-2} = 10
  Text(62.77500000000006, 13.59000000000003, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
  Text(83.7, 13.59000000000000, 'gini = 0.0\nsamples = 19\nvalue = [19, 0]'),
  Text(94.16250000000001, 95.13, X[25] \le 0.082 = 0.26 = 13 = 13 = 11, Y[25] \le 0.082 = 0.26 = 12
  Text(83.7, 67.949999999999, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
   Text(104.625, 67.9499999999999, 'X[27] <= 0.117 \setminus 100 | 0.153\\ \text{nsamples} = 12 \setminus 100 | 11, 1]'),
   Text(94.16250000000001, 40.77000000000001, 'gini = 0.0\nsamples = 11\nvalue = [11, 0]'),
  Text(115.0875, 40.77000000000001, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
   Text(88.93125, 122.31, 'gini = 0.0 \setminus samples = 1 \setminus value = [0, 1]'),
   Text(193.55625, 149.49, X[21] \le 25.67 = 0.476 = 46 = 46 = [18, 28]),
   Text(156.9375, 122.31, X[23] \le 810.3 \cdot = 0.332 \cdot = 19 \cdot = 19 \cdot = [15, 4]'),
   Text(136.01250000000002, 95.13, X[24] < 0.179 = 0.124 = 0.124 = 15 = 15 = 15
  Text(125.5500000000001, 67.9499999999999, 'gini = 0.0 \times 14 = 14 
   Text(146.475, 67.9499999999999, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
  Text(177.8625, 95.13, X[2] \le 92.79 = 0.375 = 4 = [1, 3]'),
  Text(167.4, 67.9499999999999, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]'),
  Text(219.7125, 95.13, X[1] <= 19.435 = 0.5 = 6 = 6 = [3, 3]
   Text(209.25, 67.9499999999999, 'gini = 0.0 \times = 3 \times = [3, 0]'),
  Text(230.175, 67.949999999999, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]'),
  Text(240.63750000000002, 95.13, 'gini = 0.0\nsamples = 21\nvalue = [0, 21]'),
   Text(282.4875, 176.67000000000000, 'X[1] \le 16.11 \cdot i = 0.109 \cdot i = 190 \cdot i = 190 \cdot i = 1100 \cdot i =
  Text(261.5625, 149.49, 'X[16] <= 0.034\ngini = 0.498\nsamples = 17\nvalue = [9, 8]'),
   Text(251.1000000000000, 122.31, 'gini = 0.0\nsamples = 9\nvalue = [9, 0]'),
   Text(272.02500000000003, 122.31, 'gini = 0.0\nsamples = 8\nvalue = [0, 8]'),
  Text(303.4125, 149.49, 'X[24] \leftarrow 0.088 \cdot i = 0.023 \cdot i = 173 \cdot i 
   Text(292.95, 122.31, 'gini = 0.0 \land samples = 1 \land ullet = [1, 0]'),
   Text(313.875, 122.31, X[26] < 0.18 = 0.012 = 0.012 = 172 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 =
   Text(303.4125, 95.13, X[17] \le 0.01 = 0.375 = 4 = 1, 3),
```

Text(324.33750000000003. 95.13. 'gini = 0.0\nsamples = 168\nvalue = [0. 1681')]
tree.plot\_tree(dtree.fit(data2,target), fontsize=8)

```
[\text{Text}(209.25, 203.85, 'X[20] <= 16.795 \setminus i = 0.468 \setminus samples = 569 \setminus i = [357, 212]'),
Text(136.01250000000000, 176.67000000000000, 'X[27] \le 0.136 \ngini = 0.159\nsamples = 379\nvalue = [34]
Text(78.46875, 149.49, 'X[12] \le 6.597 \text{ ngini} = 0.03 \text{ nsamples} = 333 \text{ nvalue} = [328.5]').
Text(68.00625000000001, 122.31, 'X[13] \le 38.605 \text{ ngini} = 0.024 \text{ nsamples} = 332 \text{ nvalue} = [328, 4]'),
Text(41.85, 95.13, X[14] <= 0.003 \ngini = 0.012 \nsamples = <math>319 \nvalue = [317, 2]'),
Text(20.925, 67.9499999999999, X[1] <= 19.9 \text{ ngini} = 0.245 \text{ nsamples} = 7 \text{ nvalue} = [6, 1]'),
Text(10.4625, 40.77000000000001, 'gini = 0.0\nsamples = 6\nvalue = [6, 0]'),
Text(31.387500000000003, 40.77000000000001, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(62.77500000000006, 67.949999999999, 'X[21] <= 33.27\ngini = 0.006\nsamples = 312\nvalue = [311
Text(52.3125, 40.77000000000001, 'gini = 0.0\nsamples = 292\nvalue = [292, 0]'),
Text(73.2375, 40.77000000000001, X[21] \le 33.56 = 0.095 = 20 = 20 = [19, 1]),
Text(62.77500000000006, 13.59000000000003, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(83.7, 13.59000000000000, 'gini = 0.0\nsamples = 19\nvalue = [19, 0]'),
Text(94.1625000000001, 95.13, X[28] \le 0.207 = 0.26 = 13 = 13 = 11, X[28] \le 0.207 = 0.26 = 13 = 13
Text(83.7, 67.9499999999999, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(104.625, 67.9499999999999, 'X[13] <= 39.15\ngini = 0.153\nsamples = 12\nvalue = [11, 1]'),
Text(94.16250000000001, 40.77000000000001, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(115.0875, 40.77000000000001, 'gini = 0.0\nsamples = 11\nvalue = [11, 0]'),
Text(88.93125, 122.31, 'gini = 0.0 \setminus samples = 1 \setminus value = [0, 1]'),
```

## #Conclusion-

#When we performed logistics regression the precision, recall and F1 scores are more than 50% which says that it can be considered.
#And when we applied Decision tree model the bias score is more than variance which means that it is a case of underfitting so we sho

```
Text(177.8625, 95.13, X[23] < 844.65  | 0.375 | nsamples = 4 | 1, 3]'),
Text(167.4, 67.949999999999, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]'),
Text(219.7125, 95.13, X[21] \le 28.545  | mini = 0.5 | nsamples = 6 | nvalue = [3, 3]'),
Text(209.25, 67.949999999999, 'gini = 0.0\nsamples = 3\nvalue = [3, 0]'),
Text(230.175, 67.949999999999, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]'),
Text(240.63750000000002, 95.13, 'gini = 0.0\nsamples = 21\nvalue = [0, 21]'),
Text(282.4875, 176.67000000000002, X[1] \le 16.11 \le 0.109 \le 100 \le 
Text(261.5625, 149.49, X[7] <= 0.066 \cdot ngini = 0.498 \cdot nsamples = 17 \cdot nvalue = [9, 8]'),
Text(251.1000000000000, 122.31, 'gini = 0.0\nsamples = 9\nvalue = [9, 0]'),
Text(272.02500000000003, 122.31, 'gini = 0.0\nsamples = 8\nvalue = [0, 8]'),
Text(303.4125, 149.49, 'X[24] \leftarrow 0.088 \cdot i = 0.023 \cdot i = 173 \cdot i 
Text(292.95, 122.31, 'gini = 0.0 \land samples = 1 \land ullet = [1, 0]'),
Text(313.875, 122.31, X[26] < 0.18 = 0.012 = 0.012 = 172 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 = 171 =
Text(303.4125, 95.13, X[6] <= 0.053  = 0.375 \ nsamples = 4 \ nvalue = [1, 3]'),
```

```
Text(324.337500000000003, 95.13, 'gini = 0.0\nsamples = 168\nvalue = [0, 168]')]

X[20] <= 16.795
gini = 0.468
samples = 569
value = [357, 212]
X[12] <= 6.1
gini = 0.159
value = [346, 33]
ni = 0.476
gini = 0.476
g
```