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

In [2]: df=pd.read_csv(r"C5_health care diabetes.csv")
 df

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	вмі	DiabetesPedigreeFunctio
0	6	148	72	35	0	33.6	0.62
1	1	85	66	29	0	26.6	0.35
2	8	183	64	0	0	23.3	0.67
3	1	89	66	23	94	28.1	0.16
4	0	137	40	35	168	43.1	2.28
763	10	101	76	48	180	32.9	0.17
764	2	122	70	27	0	36.8	0.34
765	5	121	72	23	112	26.2	0.24
766	1	126	60	0	0	30.1	0.34
767	1	93	70	31	0	30.4	0.31

768 rows × 9 columns

In [3]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):

#	Column	Non-Null Count	Dtype
0	Pregnancies	768 non-null	int64
1	Glucose	768 non-null	int64
2	BloodPressure	768 non-null	int64
3	SkinThickness	768 non-null	int64
4	Insulin	768 non-null	int64
5	BMI	768 non-null	float64
6	DiabetesPedigreeFunction	768 non-null	float64
7	Age	768 non-null	int64
8	Outcome	768 non-null	int64

dtypes: float64(2), int64(7)
memory usage: 54.1 KB

In [4]: df=df.dropna()

```
In [5]: | df.isnull().sum()
 Out[5]: Pregnancies
                                         0
          Glucose
                                         0
          BloodPressure
                                         0
          SkinThickness
                                         0
          Insulin
                                         0
          BMI
                                         0
          DiabetesPedigreeFunction
                                         0
                                         0
          Outcome
                                         0
          dtype: int64
 In [6]: df.describe()
 Out[6]:
                 Pregnancies
                                Glucose BloodPressure SkinThickness
                                                                       Insulin
                                                                                     BMI Diabetes
                  768.000000 768.000000
                                           768.000000
                                                         768.000000 768.000000
                                                                              768.000000
           count
           mean
                    3.845052 120.894531
                                            69.105469
                                                          20.536458
                                                                     79.799479
                                                                                31.992578
                    3.369578
                              31.972618
                                            19.355807
                                                          15.952218 115.244002
                                                                                 7.884160
             std
            min
                    0.000000
                               0.000000
                                             0.000000
                                                           0.000000
                                                                      0.000000
                                                                                 0.000000
            25%
                    1.000000
                              99.000000
                                            62.000000
                                                           0.000000
                                                                      0.000000
                                                                                27.300000
            50%
                    3.000000 117.000000
                                            72.000000
                                                          23.000000
                                                                     30.500000
                                                                                32.000000
            75%
                    6.000000 140.250000
                                            80.000000
                                                          32.000000 127.250000
                                                                                36.600000
                   17.000000 199.000000
                                           122.000000
                                                          99.000000 846.000000
                                                                                67.100000
            max
 In [7]: df.columns
 Out[7]: Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
                  'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
                 dtype='object')
 In [8]: |df['Outcome'].value_counts()
 Out[8]: 0
                500
                268
          Name: Outcome, dtype: int64
 In [9]: df1=df[['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
                  'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome']]
In [10]:
          x=df1.drop('Outcome',axis=1)
          y=df1['Outcome']
In [11]: from sklearn.model selection import train test split
          x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.70)
```

```
In [12]: from sklearn.ensemble import RandomForestClassifier
         rfc=RandomForestClassifier()
         rfc.fit(x_train,y_train)
Out[12]: RandomForestClassifier()
In [13]:
         parameters={'max_depth':[1,2,3,4,5],
                      'min_samples_leaf':[5,10,15,20,25],
                      'n_estimators':[10,20,30,40,50]}
In [14]: from sklearn.model_selection import GridSearchCV
         grid_search=GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="accu
         grid_search.fit(x_train,y_train)
Out[14]: GridSearchCV(cv=2, estimator=RandomForestClassifier(),
                      param_grid={'max_depth': [1, 2, 3, 4, 5],
                                   'min samples_leaf': [5, 10, 15, 20, 25],
                                   'n_estimators': [10, 20, 30, 40, 50]},
                      scoring='accuracy')
In [15]: grid_search.best_score_
Out[15]: 0.7765840869999445
In [16]: rfc_best=grid_search.best_estimator_
```

```
In [17]: from sklearn.tree import plot_tree
    plt.figure(figsize=(80,40))
    plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['Yes','N
```

```
Out[17]: [Text(2368.4, 1993.2, 'Pregnancies <= 4.5\ngini = 0.448\nsamples = 352\nvalue
         = [355, 182]\nclass = Yes'),
          Text(1339.2, 1630.8000000000002, 'Age <= 30.5\ngini = 0.35\nsamples = 216\nv
         alue = [263, 77]\nclass = Yes'),
          Text(793.6, 1268.4, 'Insulin <= 186.5\ngini = 0.27\nsamples = 172\nvalue =
         [229, 44] \nclass = Yes'),
          Text(396.8, 906.0, 'Glucose <= 130.5\ngini = 0.24\nsamples = 150\nvalue = [2
         04, 33]\nclass = Yes'),
          Text(198.4, 543.59999999999, 'Pregnancies <= 2.5\ngini = 0.07\nsamples = 1
         22\nvalue = [185, 7]\nclass = Yes'),
          Text(99.2, 181.199999999999, 'gini = 0.041\nsamples = 90\nvalue = [139, 3]
         \nclass = Yes'),
          Text(297.6, 181.1999999999982, 'gini = 0.147\nsamples = 32\nvalue = [46, 4]
         \nclass = Yes'),
          Text(595.2, 543.599999999999, 'Pregnancies <= 0.5\ngini = 0.488\nsamples =
         28\nvalue = [19, 26]\nclass = No'),
          Text(496.0, 181.199999999999, 'gini = 0.34\nsamples = 15\nvalue = [5, 18]
         \nclass = No'),
          Text(694.4, 181.199999999999, 'gini = 0.463\nsamples = 13\nvalue = [14, 8]
         \nclass = Yes'),
          Text(1190.4, 906.0, 'DiabetesPedigreeFunction <= 0.488\ngini = 0.424\nsample
         s = 22 \mid e = [25, 11] \mid e = Yes'),
          Text(992.0, 543.59999999999, 'Insulin <= 277.0\ngini = 0.1\nsamples = 11\n
         value = [18, 1]\nclass = Yes'),
          Text(892.8000000000001, 181.1999999999982, 'gini = 0.0\nsamples = 6\nvalue
         = [13, 0]\nclass = Yes'),
          Text(1091.2, 181.199999999999, 'gini = 0.278\nsamples = 5\nvalue = [5, 1]
         \nclass = Yes'),
          Text(1388.8, 543.59999999999, 'Age <= 23.5\ngini = 0.484\nsamples = 11\nva
         lue = [7, 10] \setminus nclass = No'),
          Text(1289.600000000001, 181.1999999999982, 'gini = 0.346\nsamples = 5\nval
         ue = [7, 2] \setminus class = Yes'),
          Text(1488.0, 181.199999999999, 'gini = 0.0\nsamples = 6\nvalue = [0, 8]\nc
         lass = No'),
          Text(1884.8, 1268.4, 'Glucose <= 114.5\ngini = 0.5\nsamples = 44\nvalue = [3
         4, 33]\nclass = Yes'),
          Text(1686.4, 906.0, 'Age <= 38.0\ngini = 0.124\nsamples = 11\nvalue = [14,
         1]\nclass = Yes'),
          Text(1587.2, 543.59999999999, 'gini = 0.0\nsamples = 6\nvalue = [9, 0]\ncl
         ass = Yes'),
          Text(1785.600000000001, 543.59999999999, 'gini = 0.278\nsamples = 5\nvalu
         e = [5, 1] \setminus class = Yes'),
          Text(2083.200000000003, 906.0, 'Age <= 33.5\ngini = 0.473\nsamples = 33\nva
         lue = [20, 32]\nclass = No'),
          Text(1984.0, 543.59999999999, 'gini = 0.0\nsamples = 7\nvalue = [0, 9]\ncl
         ass = No'),
          Text(2182.4, 543.599999999999, 'Glucose <= 154.5\ngini = 0.498\nsamples = 2
         6\nvalue = [20, 23]\nclass = No'),
          Text(2083.2000000000003, 181.1999999999982, 'gini = 0.473\nsamples = 17\nva
         lue = [16, 10] \setminus class = Yes'),
          Text(2281.6, 181.199999999999, 'gini = 0.36\nsamples = 9\nvalue = [4, 13]
         \nclass = No'),
          Text(3397.6, 1630.800000000000, 'Glucose <= 128.5\ngini = 0.498\nsamples =
         136\nvalue = [92, 105]\nclass = No'),
          Text(2876.8, 1268.4, 'SkinThickness <= 37.5\ngini = 0.427\nsamples = 72\nval
         ue = [74, 33]\nclass = Yes'),
          Text(2678.4, 906.0, 'BMI <= 39.05\ngini = 0.447\nsamples = 59\nvalue = [61,
```

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31]\nclass = Yes'),
  Text(2579.2000000000003, 543.599999999999, 'Insulin <= 24.5 \neq 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.415 = 0.
samples = 54\nvalue = [60, 25]\nclass = Yes'),
 Text(2480.0, 181.199999999999, 'gini = 0.438\nsamples = 43\nvalue = [46, 2]
2]\nclass = Yes'),
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3]\nclass = Yes'),
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class = No'),
  Text(3075.2000000000003, 906.0, 'DiabetesPedigreeFunction <= 0.321\ngini =
0.231\nsamples = 13\nvalue = [13, 2]\nclass = Yes'),
  Text(2976.0, 543.59999999999, 'gini = 0.0\nsamples = 8\nvalue = [10, 0]\nc
lass = Yes'),
  Text(3174.4, 543.59999999999, 'gini = 0.48\nsamples = 5\nvalue = [3, 2]\nc
lass = Yes'),
  Text(3918.4, 1268.4, 'BloodPressure <= 75.5\ngini = 0.32\nsamples = 64\nvalu
e = [18, 72] \setminus nclass = No'),
 Text(3571.2000000000003, 906.0, 'Glucose <= 166.5\ngini = 0.402\nsamples = 3
1\nvalue = [12, 31]\nclass = No'),
  Text(3372.8, 543.59999999999, 'Insulin <= 132.5\ngini = 0.493\nsamples = 1
9\nvalue = [11, 14]\nclass = No'),
  Text(3273.6, 181.199999999999, 'gini = 0.415\nsamples = 13\nvalue = [5, 1]
2]\nclass = No'),
  Text(3472.0, 181.199999999999, 'gini = 0.375\nsamples = 6\nvalue = [6, 2]
\nclass = Yes'),
  Text(3769.6, 543.59999999999, 'BMI <= 33.25\ngini = 0.105\nsamples = 12\nv
alue = [1, 17]\nclass = No'),
  Text(3670.4, 181.199999999999, 'gini = 0.0\nsamples = 7\nvalue = [0, 12]\n
class = No'),
  Text(3868.8, 181.199999999999, 'gini = 0.278\nsamples = 5\nvalue = [1, 5]
\nclass = No'),
 Text(4265.6, 906.0, 'Insulin <= 157.5\ngini = 0.223\nsamples = 33\nvalue =
[6, 41] \setminus class = No'),
 Text(4166.40000000001, 543.59999999999, 'Age <= 47.5\ngini = 0.284\nsampl
es = 24\nvalue = [6, 29]\nclass = No'),
 Text(4067.2000000000003, 181.1999999999982, 'gini = 0.351\nsamples = 17\nva
lue = [5, 17]\nclass = No'),
 Text(4265.6, 181.199999999999, 'gini = 0.142\nsamples = 7\nvalue = [1, 12]
\nclass = No'),
 Text(4364.8, 543.59999999999, 'gini = 0.0\nsamples = 9\nvalue = [0, 12]\nc
lass = No')]
```

