```
In [1]:
         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
In [2]: from sklearn.linear_model import LogisticRegression
In [3]: df=pd.read_csv("C5 health.csv").dropna()
         df
Out[3]:
               Pregnancies Glucose BloodPressure SkinThickness Insulin
                                                                         BMI DiabetesPedigreeFunctio
                         6
                                                                         33.6
            0
                                148
                                               72
                                                              35
                                                                      0
                                                                                                 0.62
            1
                         1
                                 85
                                               66
                                                              29
                                                                      0 26.6
                                                                                                 0.35
            2
                         8
                                                                        23.3
                                                                                                 0.67
                                183
                                               64
                                                               0
                                                                      0
            3
                                 89
                                               66
                                                              23
                                                                         28.1
                                                                                                 0.16
            4
                         0
                                137
                                               40
                                                              35
                                                                    168 43.1
                                                                                                 2.28
                                 ...
          763
                        10
                                101
                                                                     180 32.9
                                                                                                 0.17
                                               76
                                                              48
                         2
          764
                                122
                                               70
                                                              27
                                                                      0
                                                                        36.8
                                                                                                 0.34
          765
                         5
                                121
                                               72
                                                              23
                                                                     112 26.2
                                                                                                 0.24
                         1
          766
                                126
                                               60
                                                               0
                                                                      0 30.1
                                                                                                 0.34
          767
                                 93
                                               70
                                                              31
                                                                      0 30.4
                                                                                                 0.31
```

768 rows × 9 columns

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

```
In [5]: df.info()
         <class 'pandas.core.frame.DataFrame'>
         Int64Index: 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
                                         768 non-null
                                                          int64
                                         768 non-null
          8
              Outcome
                                                          int64
         dtypes: float64(2), int64(7)
         memory usage: 60.0 KB
 In [6]: | feature_matrix = df[['Pregnancies','Glucose','BloodPressure','SkinThickness','
         target vector = df['Outcome']
 In [7]: | feature_matrix.shape
 Out[7]: (768, 8)
 In [8]: | target_vector.shape
 Out[8]: (768,)
 In [9]: | from sklearn.preprocessing import StandardScaler
In [10]: | fs = StandardScaler().fit_transform(feature_matrix)
In [11]: logr = LogisticRegression()
         logr.fit(fs,target_vector)
Out[11]: LogisticRegression()
In [12]: feature matrix.shape
Out[12]: (768, 8)
In [13]: |target_vector.shape
Out[13]: (768,)
In [14]: from sklearn.preprocessing import StandardScaler
         fs = StandardScaler().fit_transform(feature_matrix)
```

```
In [16]: logr = LogisticRegression()
   logr.fit(fs,target_vector)
Out[16]: LogisticRegression()
In [17]: observation=df[['Pregnancies','Glucose','BloodPressure','SkinThickness','Insul
In [18]:
   prediction = logr.predict(observation)
   prediction
1, 1, 1,
      1, 1, 1, 1, 1, 1, 1, 1,
                     1, 1, 1, 1, 1, 1, 1,
      1, 1, 1, 1, 1, 1, 1, 1,
                    1,
                     1, 1, 1, 1, 1,
      1, 1, 1, 1, 1, 1, 1,
                   1,
                    1, 1, 1, 1, 1, 1,
      1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                     1, 1, 1, 1, 1, 1, 1, 1,
      1, 1, 1, 1, 1, 1, 1,
                    1, 1, 1, 1, 1, 1,
      In [19]: logr.classes
Out[19]: array([0, 1], dtype=int64)
In [20]: logr.predict_proba(observation)[0][1]
Out[20]: 1.0
```

Random Forest

```
In [23]: g1={'Outcome':{"1":1, "0":2}}
df=df.replace(g1)
df
```

Out[23]:		Dreanancies	Glucose	BloodPressure	SkinThickness	Inculin	ВМІ	DiabetesPedigreeFunction
		6	148	72	35		33.6	0.62
	1	1	85	66	29	0		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 rc	ws × 9 colur	nns					
	4							*
In [25]:	<pre>from sklearn.ensemble import RandomForestClassifier rfc = RandomForestClassifier() rfc.fit(x_train,y_train)</pre>							
Out[25]:	RandomForestClassifier()							
In [26]:	<pre>parameters = {'max_depth':[1,2,3,4,5],'min_samples_leaf':[5,10,15,20,25],</pre>							
In [27]:	<pre>from sklearn.model_selection import GridSearchCV grid_search = GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="a" grid_search.fit(x_train,y_train)</pre>							
Out[27]:	<pre>GridSearchCV(cv=2, estimator=RandomForestClassifier(),</pre>							
In [28]:	grid_	search.bes	t_score_	_				

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Out[28]: 0.7821256172668257

In [29]: rfc_best = grid_search.best_estimator_

```
In [30]: from sklearn.tree import plot_tree
    plt.figure(figsize = (80,40,))
    plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['Yes',']
```

```
Out[30]: [Text(3026.076923076923, 1993.2, 'Pregnancies <= 6.5\ngini = 0.456\nsamples =</pre>
                      347\nvalue = [348, 189]\nclass = Yes'),
                       Text(2103.230769230769, 1630.8000000000002, 'BMI <= 30.85\ngini = 0.405\nsam
                      ples = 273\nvalue = [305, 120]\nclass = Yes'),
                       Text(1287.6923076923076, 1268.4, 'Age <= 28.5\ngini = 0.154\nsamples = 127\n
                      value = [174, 16]\nclass = Yes'),
                       Text(686.7692307692307, 906.0, 'SkinThickness <= 5.0\ngini = 0.043\nsamples
                      = 89\nvalue = [133, 3]\nclass = Yes'),
                       Text(343.38461538461536, 543.59999999999, 'Glucose <= 109.5\ngini = 0.108
                      \nsamples = 25\nvalue = [33, 2]\nclass = Yes'),
                       Text(171.69230769230768, 181.1999999999982, 'gini = 0.0\nsamples = 14\nvalu
                      e = [19, 0] \setminus class = Yes'),
                       Text(515.0769230769231, 181.1999999999982, 'gini = 0.219\nsamples = 11\nval
                     ue = [14, 2]\nclass = Yes'),
                       Text(1030.1538461538462, 543.599999999999, 'Age <= 24.5\ngini = 0.02\nsampl
                      es = 64\nvalue = [100, 1]\nclass = Yes'),
                       Text(858.4615384615383, 181.1999999999999, 'gini = 0.0\nsamples = 53\nvalue
                      = [85, 0]\nclass = Yes'),
                       Text(1201.8461538461538, 181.19999999999982, 'gini = 0.117\nsamples = 11\nva
                      lue = [15, 1]\nclass = Yes'),
                       Text(1888.6153846153845, 906.0, 'Insulin <= 11.5\ngini = 0.366\nsamples = 38

    \text{(nvalue = [41, 13]} \\
                       Text(1716.9230769230767, 543.59999999999, 'DiabetesPedigreeFunction <= 0.2
                      58\ngini = 0.301\nsamples = 28\nvalue = [31, 7]\nclass = Yes'),
                       Text(1545.230769230769, 181.1999999999982, 'gini = 0.117\nsamples = 11\nval
                     ue = [15, 1]\nclass = Yes'),
                       Text(1888.6153846153845, 181.19999999999982, 'gini = 0.397\nsamples = 17\nva
                      lue = [16, 6]\nclass = Yes'),
                       Text(2060.3076923076924, 543.599999999999, 'gini = 0.469\nsamples = 10\nval
                      ue = [10, 6]\nclass = Yes'),
                       Text(2918.7692307692305, 1268.4, 'BMI <= 45.45\ngini = 0.493\nsamples = 146
                      \nvalue = [131, 104]\nclass = Yes'),
                       Text(2747.076923076923, 906.0, 'SkinThickness <= 6.5\ngini = 0.482\nsamples
                      = 136\nvalue = [130, 89]\nclass = Yes'),
                       Text(2403.6923076923076, 543.59999999999, 'BMI <= 35.5\ngini = 0.494\nsamp
                      les = 31\nvalue = [24, 30]\nclass = No'),
                       Text(2232.0, 181.199999999999, 'gini = 0.48\nsamples = 19\nvalue = [18, 1
                     2]\nclass = Yes'),
                       Text(2575.3846153846152, 181.19999999999982, 'gini = 0.375\nsamples = 12\nva
                      lue = [6, 18]\nclass = No'),
                       Text(3090.461538461538, 543.599999999999, 'Pregnancies <= 3.5\ngini = 0.459
                      \nsamples = 105 \nvalue = [106, 59] \nclass = Yes'),
                       Text(2918.7692307692305, 181.19999999999982, 'gini = 0.479\nsamples = 80\nva
                      lue = [74, 49] \setminus class = Yes'),
                       Text(3262.1538461538457, 181.19999999999982, 'gini = 0.363\nsamples = 25\nva
                      lue = [32, 10]\nclass = Yes'),
                       Text(3090.461538461538, 906.0, 'gini = 0.117\nsamples = 10\nvalue = [1, 15]
                      \nclass = No'),
                       Text(3948.9230769230767, 1630.8000000000000, 'BMI <= 26.3\ngini = 0.473\nsam
                      ples = 74\nvalue = [43, 69]\nclass = No'),
                       Text(3777.230769230769, 1268.4, 'gini = 0.095\nsamples = 12\nvalue = [19, 1]
                      \nclass = Yes'),
                       Text(4120.615384615385, 1268.4, 'BloodPressure <= 83.0\ngini = 0.386\nsample
                      s = 62 \setminus e = [24, 68] \setminus e = No'),
                       Text(3948.9230769230767, 906.0, 'Insulin <= 107.5\ngini = 0.424\nsamples = 4
Loading [MathJax]/exects May safe. [22, 50] \nclass = No'),
                        Text(3///.230769230769, 543.599999999999, 'Glucose <= 105.0\ngini = 0.489\n
```

localhost:8888/notebooks/health (C5).ipynb

```
samples = 30\nvalue = [17, 23]\nclass = No'),
  Text(3605.5384615384614, 181.1999999999982, 'gini = 0.375\nsamples = 10\nva
lue = [9, 3]\nclass = Yes'),
  Text(3948.9230769230767, 181.1999999999982, 'gini = 0.408\nsamples = 20\nva
lue = [8, 20]\nclass = No'),
  Text(4120.615384615385, 543.599999999999, 'gini = 0.264\nsamples = 18\nvalu
e = [5, 27]\nclass = No'),
  Text(4292.307692307692, 906.0, 'gini = 0.18\nsamples = 14\nvalue = [2, 18]\n
class = No')]
```

