

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")

df=pd.read_csv("diabetes.csv")
df
```

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

768 rows × 9 columns

```
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

df['Pregnancies'].unique()

array([ 6,  1,  8,  0,  5,  3, 10,  2,  4,  7,  9, 11, 13, 15, 17, 12, 14])

df['Glucose'].unique()

array([148,  85, 183,  89, 137, 116,  78, 115, 197, 125, 110, 168, 139,
       189, 166, 100, 118, 107, 103, 126,  99, 196, 119, 143, 147,  97,
       145, 117, 109, 158,  88,  92, 122, 138, 102,  90, 111, 180, 133,
       106, 171, 159, 146,  71, 105, 101, 176, 150,  73, 187,  84,  44,
       141, 114,  95, 129,  79,  0,  62, 131, 112, 113,  74,  83, 136,
       80, 123,  81, 134, 142, 144,  93, 163, 151,  96, 155,  76, 160,
       124, 162, 132, 120, 173, 170, 128, 108, 154,  57, 156, 153, 188,
       152, 104,  87,  75, 179, 130, 194, 181, 135, 184, 140, 177, 164,
       91, 165,  86, 193, 191, 161, 167,  77, 182, 157, 178,  61,  98,
       127,  82,  72, 172,  94, 175, 195,  68, 186, 198, 121,  67, 174,
       199,  56, 169, 149,  65, 190])

df['BloodPressure'].unique()

array([ 72,  66,  64,  40,  74,  50,  0,  70,  96,  92,  80,  60,  84,
       30,  88,  90,  94,  76,  82,  75,  58,  78,  68, 110,  56,  62,
       85,  86,  48,  44,  65, 108,  55, 122,  54,  52,  98, 104,  95,
       46, 102, 100,  61,  24,  38, 106, 114])

df['SkinThickness'].unique()
```

```

array([35, 29, 0, 23, 32, 45, 19, 47, 38, 30, 41, 33, 26, 15, 36, 11, 31,
       37, 42, 25, 18, 24, 39, 27, 21, 34, 10, 60, 13, 20, 22, 28, 54, 40,
       51, 56, 14, 17, 50, 44, 12, 46, 16, 7, 52, 43, 48, 8, 49, 63, 99])

df['Insulin'].unique()

array([ 0, 94, 168, 88, 543, 846, 175, 230, 83, 96, 235, 146, 115,
       140, 110, 245, 54, 192, 207, 70, 240, 82, 36, 23, 300, 342,
       304, 142, 128, 38, 100, 90, 270, 71, 125, 176, 48, 64, 228,
       76, 220, 40, 152, 18, 135, 495, 37, 51, 99, 145, 225, 49,
       50, 92, 325, 63, 284, 119, 204, 155, 485, 53, 114, 105, 285,
       156, 78, 130, 55, 58, 160, 210, 318, 44, 190, 280, 87, 271,
       129, 120, 478, 56, 32, 744, 370, 45, 194, 680, 402, 258, 375,
       150, 67, 57, 116, 278, 122, 545, 75, 74, 182, 360, 215, 184,
       42, 132, 148, 180, 205, 85, 231, 29, 68, 52, 255, 171, 73,
       108, 43, 167, 249, 293, 66, 465, 89, 158, 84, 72, 59, 81,
       196, 415, 275, 165, 579, 310, 61, 474, 170, 277, 60, 14, 95,
       237, 191, 328, 250, 480, 265, 193, 79, 86, 326, 188, 106, 65,
       166, 274, 77, 126, 330, 600, 185, 25, 41, 272, 321, 144, 15,
       183, 91, 46, 440, 159, 540, 200, 335, 387, 22, 291, 392, 178,
       127, 510, 16, 112])

df['BMI'].unique()

array([33.6, 26.6, 23.3, 28.1, 43.1, 25.6, 31. , 35.3, 30.5, 0. , 37.6,
       38. , 27.1, 30.1, 25.8, 30. , 45.8, 29.6, 43.3, 34.6, 39.3, 35.4,
       39.8, 29. , 36.6, 31.1, 39.4, 23.2, 22.2, 34.1, 36. , 31.6, 24.8,
       19.9, 27.6, 24. , 33.2, 32.9, 38.2, 37.1, 34. , 40.2, 22.7, 45.4,
       27.4, 42. , 29.7, 28. , 39.1, 19.4, 24.2, 24.4, 33.7, 34.7, 23. ,
       37.7, 46.8, 40.5, 41.5, 25. , 25.4, 32.8, 32.5, 42.7, 19.6, 28.9,
       28.6, 43.4, 35.1, 32. , 24.7, 32.6, 43.2, 22.4, 29.3, 24.6, 48.8,
       32.4, 38.5, 26.5, 19.1, 46.7, 23.8, 33.9, 20.4, 28.7, 49.7, 39. ,
       26.1, 22.5, 39.6, 29.5, 34.3, 37.4, 33.3, 31.2, 28.2, 53.2, 34.2,
       26.8, 55. , 42.9, 34.5, 27.9, 38.3, 21.1, 33.8, 30.8, 36.9, 39.5,
       27.3, 21.9, 40.6, 47.9, 50. , 25.2, 40.9, 37.2, 44.2, 29.9, 31.9,
       28.4, 43.5, 32.7, 67.1, 45. , 34.9, 27.7, 35.9, 22.6, 33.1, 30.4,
       52.3, 24.3, 22.9, 34.8, 30.9, 40.1, 23.9, 37.5, 35.5, 42.8, 42.6,
       41.8, 35.8, 37.8, 28.8, 23.6, 35.7, 36.7, 45.2, 44. , 46.2, 35. ,
       43.6, 44.1, 18.4, 29.2, 25.9, 32.1, 36.3, 40. , 25.1, 27.5, 45.6,
       27.8, 24.9, 25.3, 37.9, 27. , 26. , 38.7, 20.8, 36.1, 30.7, 32.3,
       52.9, 21. , 39.7, 25.5, 26.2, 19.3, 38.1, 23.5, 45.5, 23.1, 39.9,
       36.8, 21.8, 41. , 42.2, 34.4, 27.2, 36.5, 29.8, 39.2, 38.4, 36.2,
       48.3, 20. , 22.3, 45.7, 23.7, 22.1, 42.1, 42.4, 18.2, 26.4, 45.3,
       37. , 24.5, 32.2, 59.4, 21.2, 26.7, 30.2, 46.1, 41.3, 38.8, 35.2,
       42.3, 40.7, 46.5, 33.5, 37.3, 30.3, 26.3, 21.7, 36.4, 28.5, 26.9,
       38.6, 31.3, 19.5, 20.1, 40.8, 23.4, 28.3, 38.9, 57.3, 35.6, 49.6,
       44.6, 24.1, 44.5, 41.2, 49.3, 46.3])

df['DiabetesPedigreeFunction'].unique()

array([0.627, 0.351, 0.672, 0.167, 2.288, 0.201, 0.248, 0.134, 0.158,
       0.232, 0.191, 0.537, 1.441, 0.398, 0.587, 0.484, 0.551, 0.254,
       0.183, 0.529, 0.704, 0.388, 0.451, 0.263, 0.205, 0.257, 0.487,
       0.245, 0.337, 0.546, 0.851, 0.267, 0.188, 0.512, 0.966, 0.42 ,
       0.665, 0.503, 1.39 , 0.271, 0.696, 0.235, 0.721, 0.294, 1.893,
       0.564, 0.586, 0.344, 0.305, 0.491, 0.526, 0.342, 0.467, 0.718,
       0.962, 1.781, 0.173, 0.304, 0.27 , 0.699, 0.258, 0.203, 0.855,
       0.845, 0.334, 0.189, 0.867, 0.411, 0.583, 0.231, 0.396, 0.14 ,
       0.391, 0.37 , 0.307, 0.102, 0.767, 0.237, 0.227, 0.698, 0.178,
       0.324, 0.153, 0.165, 0.443, 0.261, 0.277, 0.761, 0.255, 0.13 ,
       0.323, 0.356, 0.325, 1.222, 0.179, 0.262, 0.283, 0.93 , 0.801,
       0.207, 0.287, 0.336, 0.247, 0.199, 0.543, 0.192, 0.588, 0.539,
       0.22 , 0.654, 0.223, 0.759, 0.26 , 0.404, 0.186, 0.278, 0.496,
       0.452, 0.403, 0.741, 0.361, 1.114, 0.457, 0.647, 0.088, 0.597,
       0.532, 0.703, 0.159, 0.268, 0.286, 0.318, 0.272, 0.572, 0.096,
       1.4 , 0.218, 0.085, 0.399, 0.432, 1.189, 0.687, 0.137, 0.637,
       0.833, 0.229, 0.817, 0.204, 0.368, 0.743, 0.722, 0.256, 0.709,
       0.471, 0.495, 0.18 , 0.542, 0.773, 0.678, 0.719, 0.382, 0.319,
       0.19 , 0.956, 0.084, 0.725, 0.299, 0.244, 0.745, 0.615, 1.321,
       0.64 , 0.142, 0.374, 0.383, 0.578, 0.136, 0.395, 0.187, 0.905,
       0.15 , 0.874, 0.236, 0.787, 0.407, 0.605, 0.151, 0.289, 0.355,
       0.29 , 0.375, 0.164, 0.431, 0.742, 0.514, 0.464, 1.224, 1.072,
       0.805, 0.209, 0.666, 0.101, 0.198, 0.652, 2.329, 0.089, 0.645,
       0.238, 0.394, 0.293, 0.479, 0.686, 0.831, 0.582, 0.446, 0.402,
       1.318, 0.329, 1.213, 0.427, 0.282, 0.143, 0.38 , 0.284, 0.249,
       0.926, 0.557, 0.092, 0.655, 1.353, 0.612, 0.2 , 0.226, 0.997,
       0.933, 1.101, 0.078, 0.24 , 1.136, 0.128, 0.422, 0.251, 0.677,
       0.296, 0.454, 0.744, 0.881, 0.28 , 0.259, 0.619, 0.808, 0.34 ,
       0.434, 0.757, 0.613, 0.692, 0.52 , 0.412, 0.84 , 0.839, 0.156,
       0.215, 0.326, 1.391, 0.875, 0.313, 0.433, 0.626, 1.127, 0.315,
       0.345, 0.129, 0.527, 0.197, 0.731, 0.148, 0.123, 0.127, 0.122,
       1.476, 0.166, 0.932, 0.343, 0.893, 0.331, 0.472, 0.673, 0.389,
       0.485, 0.349, 0.279, 0.346, 0.252, 0.243, 0.58 , 0.559, 0.302,
       0.569, 0.378, 0.385, 0.499, 0.306, 0.234, 2.137, 1.731, 0.545,
       0.225, 0.816, 0.528, 0.509, 1.021, 0.821, 0.947, 1.268, 0.221,
       0.66 , 0.239, 0.949, 0.444, 0.463, 0.803, 1.6 , 0.944, 0.196,

```

```
0.241, 0.161, 0.135, 0.376, 1.191, 0.702, 0.674, 1.076, 0.534,
1.095, 0.554, 0.624, 0.219, 0.507, 0.561, 0.421, 0.516, 0.264,
0.328, 0.233, 0.108, 1.138, 0.147, 0.727, 0.435, 0.497, 0.23 ,
0.955, 2.42 , 0.658, 0.33 , 0.51 , 0.285, 0.415, 0.381, 0.832,
0.498, 0.212, 0.364, 1.001, 0.46 , 0.733, 0.416, 0.705, 1.022,
0.269, 0.6 , 0.571, 0.607, 0.17 , 0.21 , 0.126, 0.711, 0.466,
0.162, 0.419, 0.63 , 0.365, 0.536, 1.159, 0.629, 0.292, 0.145,
1.144, 0.174, 0.547, 0.163, 0.738, 0.314, 0.968, 0.409, 0.297,
0.525, 0.154, 0.771, 0.107, 0.493, 0.717, 0.917, 0.501, 1.251,
0.735, 0.804, 0.661, 0.549, 0.825, 0.423, 1.034, 0.16 , 0.341,
0.68 , 0.591, 0.3 , 0.121, 0.502, 0.401, 0.601, 0.748, 0.338,
0.43 , 0.892, 0.813, 0.693, 0.575, 0.371, 0.206, 0.417, 1.154,
0.925, 0.175, 1.699, 0.682, 0.194, 0.4 , 0.1 , 1.258, 0.482,
0.138, 0.593, 0.878, 0.157, 1.282, 0.141, 0.246, 1.698, 1.461,
0.347, 0.362, 0.393, 0.144, 0.732, 0.115, 0.465, 0.649, 0.871,
0.149, 0.695, 0.303, 0.61 , 0.73 , 0.447, 0.455, 0.133, 0.155,
1.162, 1.292, 0.182, 1.394, 0.217, 0.631, 0.88 , 0.614, 0.332,
0.366, 0.181, 0.828, 0.335, 0.856, 0.886, 0.439, 0.253, 0.598,
0.904, 0.483, 0.565, 0.118, 0.177, 0.176, 0.295, 0.441, 0.352,
0.826, 0.97 , 0.595, 0.317, 0.265, 0.646, 0.426, 0.56 , 0.515,
0.453, 0.785, 0.734, 1.174, 0.488, 0.358, 1.096, 0.408, 1.182,
```

```
df['Age'].unique()

array([50, 31, 32, 21, 33, 30, 26, 29, 53, 54, 34, 57, 59, 51, 27, 41, 43,
       22, 38, 60, 28, 45, 35, 46, 56, 37, 48, 40, 25, 24, 58, 42, 44, 39,
       36, 23, 61, 69, 62, 55, 65, 47, 52, 66, 49, 63, 67, 72, 81, 64, 70,
       68])

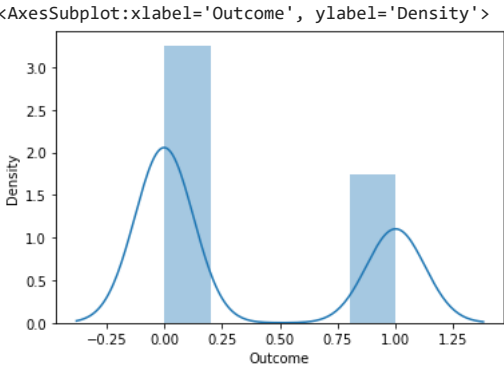
# there are 5 ('Glucose','BloodPressure','SkinThickness','Insulin','BMI' ) columns contain 0 values which are invalid so replace 0 with r

df[['Glucose','BloodPressure','SkinThickness','Insulin','BMI']]=df[['Glucose','BloodPressure','SkinThickness','Insulin','BMI']].replace(0

df.isnull().sum()

Pregnancies      0
Glucose           5
BloodPressure     35
SkinThickness    227
Insulin          374
BMI              11
DiabetesPedigreeFunction  0
Age              0
Outcome          0
dtype: int64

sns.distplot(df['Outcome'])
```



```
df.describe()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BM
count	768.000000	763.000000	733.000000	541.000000	394.000000	757.000000
mean	3.845052	121.686763	72.405184	29.153420	155.548223	32.45746
std	3.369578	30.535641	12.382158	10.476982	118.775855	6.92498
min	0.000000	44.000000	24.000000	7.000000	14.000000	18.20000
25%	1.000000	99.000000	64.000000	22.000000	76.250000	27.50000
50%	3.000000	117.000000	72.000000	29.000000	125.000000	32.30000
75%	6.000000	141.000000	80.000000	36.000000	190.000000	36.60000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.10000

```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.30,random_state=12)
```

```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
xtrain=sc.fit_transform(xtrain)
xtest=sc.transform(xtest)
```

```
import tensorflow as tf
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
from sklearn.metrics import classification_report
```

```
ann=Sequential()
```

```
ann.add(Dense(units=30,activation='relu'))
ann.add(Dense(units=1,activation="sigmoid"))
```

```
ann.compile(optimizer="adam",loss="binary_crossentropy",metrics=["accuracy"])
```

```
ann.fit(xtrain,ytrain,batch_size=40,epochs=100)
```

```
Epoch 1/100
14/14 [=====] - 0s 2ms/step - loss: 0.2998 - accuracy: 0.8659
Epoch 2/100
14/14 [=====] - 0s 2ms/step - loss: 0.3013 - accuracy: 0.8659
Epoch 3/100
14/14 [=====] - 0s 2ms/step - loss: 0.3003 - accuracy: 0.8696
Epoch 4/100
14/14 [=====] - 0s 3ms/step - loss: 0.2992 - accuracy: 0.8678
Epoch 5/100
14/14 [=====] - 0s 3ms/step - loss: 0.2994 - accuracy: 0.8678
Epoch 6/100
14/14 [=====] - 0s 2ms/step - loss: 0.2982 - accuracy: 0.8622
Epoch 7/100
14/14 [=====] - 0s 2ms/step - loss: 0.2990 - accuracy: 0.8678
Epoch 8/100
14/14 [=====] - 0s 2ms/step - loss: 0.2968 - accuracy: 0.8659
Epoch 9/100
14/14 [=====] - 0s 2ms/step - loss: 0.2970 - accuracy: 0.8678
Epoch 10/100
14/14 [=====] - 0s 2ms/step - loss: 0.2961 - accuracy: 0.8641
Epoch 11/100
14/14 [=====] - 0s 2ms/step - loss: 0.2949 - accuracy: 0.8734
Epoch 12/100
14/14 [=====] - 0s 2ms/step - loss: 0.2948 - accuracy: 0.8641
Epoch 13/100
14/14 [=====] - 0s 2ms/step - loss: 0.2937 - accuracy: 0.8678
Epoch 14/100
14/14 [=====] - 0s 2ms/step - loss: 0.2946 - accuracy: 0.8696
Epoch 15/100
14/14 [=====] - 0s 2ms/step - loss: 0.2931 - accuracy: 0.8696
Epoch 16/100
14/14 [=====] - 0s 2ms/step - loss: 0.2932 - accuracy: 0.8771
Epoch 17/100
14/14 [=====] - 0s 3ms/step - loss: 0.2919 - accuracy: 0.8752
Epoch 18/100
14/14 [=====] - 0s 3ms/step - loss: 0.2912 - accuracy: 0.8696
Epoch 19/100
14/14 [=====] - 0s 2ms/step - loss: 0.2903 - accuracy: 0.8715
Epoch 20/100
14/14 [=====] - 0s 2ms/step - loss: 0.2903 - accuracy: 0.8678
Epoch 21/100
14/14 [=====] - 0s 3ms/step - loss: 0.2891 - accuracy: 0.8696
Epoch 22/100
14/14 [=====] - 0s 3ms/step - loss: 0.2895 - accuracy: 0.8752
Epoch 23/100
14/14 [=====] - 0s 3ms/step - loss: 0.2892 - accuracy: 0.8696
Epoch 24/100
14/14 [=====] - 0s 2ms/step - loss: 0.2891 - accuracy: 0.8734
Epoch 25/100
14/14 [=====] - 0s 2ms/step - loss: 0.2879 - accuracy: 0.8734
Epoch 26/100
14/14 [=====] - 0s 2ms/step - loss: 0.2859 - accuracy: 0.8715
Epoch 27/100
14/14 [=====] - 0s 2ms/step - loss: 0.2860 - accuracy: 0.8734
Epoch 28/100
14/14 [=====] - 0s 2ms/step - loss: 0.2853 - accuracy: 0.8734
Epoch 29/100
14/14 [=====] - 0s 2ms/step - loss: 0.2850 - accuracy: 0.8696
```

[illegible]

	precision	recall	f1-score	support
0	1.00	0.64	0.78	231
1	0.00	0.00	0.00	0
accuracy			0.64	231
macro avg	0.50	0.32	0.39	231
weighted avg	1.00	0.64	0.78	231

