HealthCareDiabetes

September 27, 2020

1 import os

os.getcwd()

[1]:
```
#impoorting Important Libraries and loading dataset
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
from sklearn import metrics

data = pd.read_csv(r"/home/sunny/Data Science -Python/capstone 2/
 ↪HealthCareDiabetes.csv")
data.head()
```

[1]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
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

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
```

2 Descriptive Analysis and EDA

[2]:
```python
print( "Shape:",data.shape)
print( "Size",data.size)

print("Columns", data.columns)
```

```
Shape: (768, 9)
Size 6912
Columns Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

[3]:
```python
#unique values in dataset
data.nunique()
```

[3]:
```
Pregnancies                  17
Glucose                     136
BloodPressure                47
SkinThickness                51
Insulin                     186
BMI                         248
DiabetesPedigreeFunction    517
Age                          52
Outcome                       2
dtype: int64
```

[4]:
```python
#dataset Dispersion
data.describe()
```

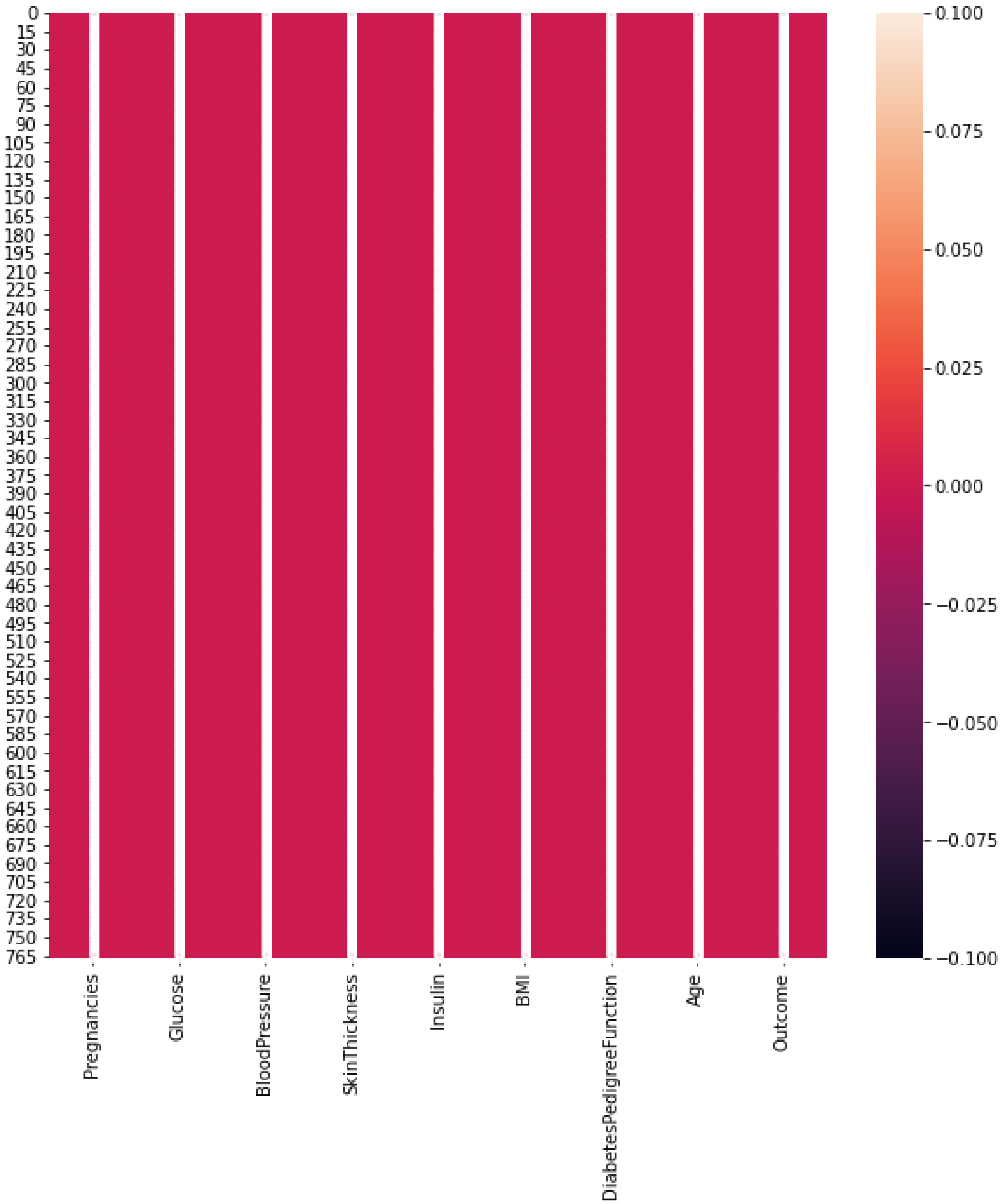
[4]:
```
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  768.000000     768.000000     768.000000  768.000000
mean      3.845052  120.894531      69.105469      20.536458   79.799479
std       3.369578   31.972618      19.355807      15.952218  115.244002
min       0.000000    0.000000       0.000000       0.000000    0.000000
25%       1.000000   99.000000      62.000000       0.000000    0.000000
50%       3.000000  117.000000      72.000000      23.000000   30.500000
75%       6.000000  140.250000      80.000000      32.000000  127.250000
max      17.000000  199.000000     122.000000      99.000000  846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
min      0.000000                  0.078000   21.000000    0.000000
25%     27.300000                  0.243750   24.000000    0.000000
```

```
50%      32.000000                    0.372500   29.000000   0.000000
75%      36.600000                    0.626250   41.000000   1.000000
max      67.100000                    2.420000   81.000000   1.000000
```

[5]:
```python
#dataset with null value
data.isnull().sum()
```

[5]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

[6]:
```python
#Heatmap of dataset with null value
plt.figure(figsize=(10,10))
sns.heatmap(data.isnull(),annot=True,xticklabels=True)
plt.show()
```



Great! No null Value in Dataset

[7]:
```
#Dataset Info and its datatype
data.info()
```

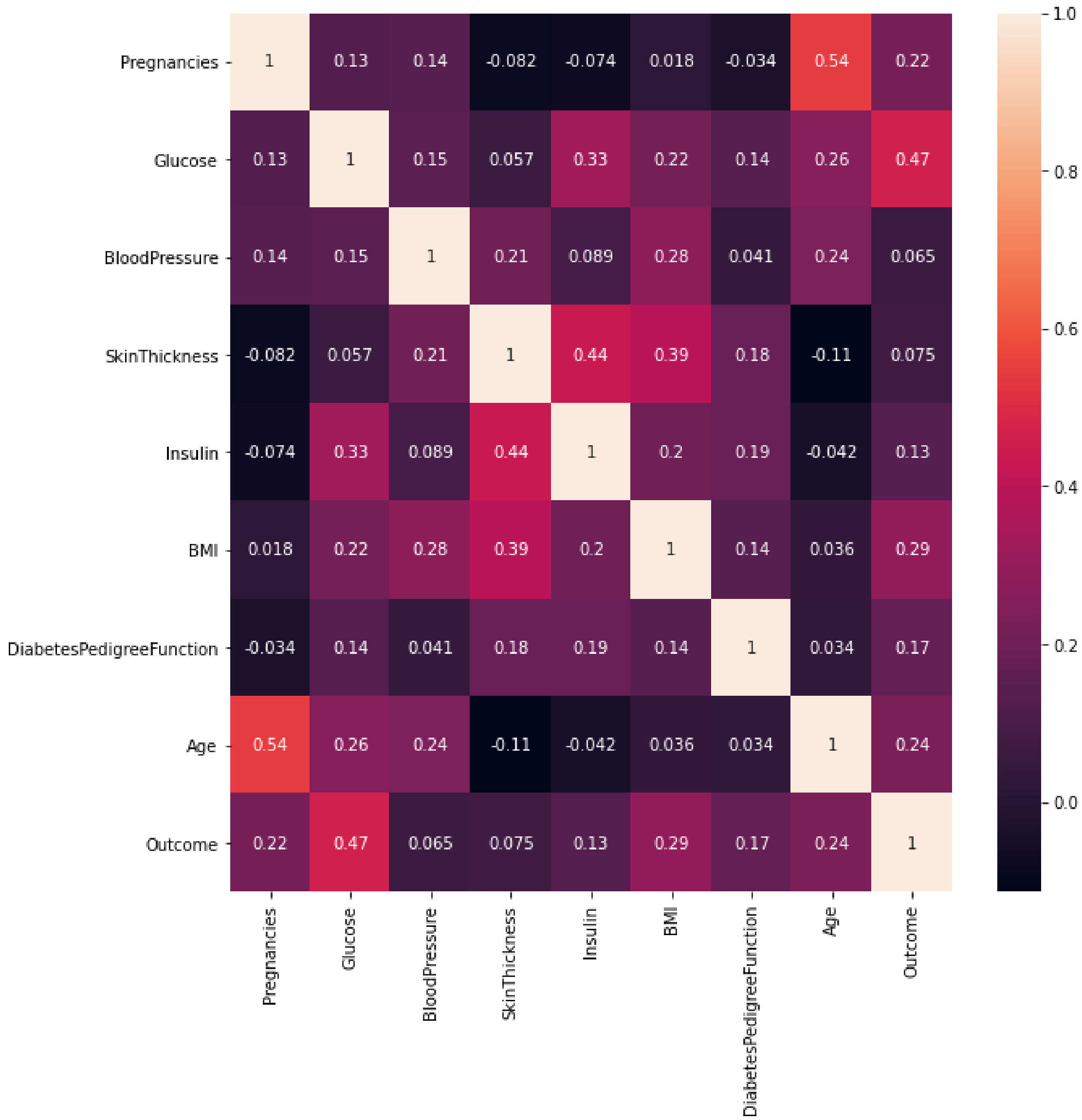
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
```

```
 #   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
```

Seems ,no Categorical Random variable

2.1 Analyzing Relationships between Variables

[8]:
```python
#Heatmap with Correlation of values
plt.figure(figsize=(10,10))
sns.heatmap(data.corr(),annot=True,xticklabels=True,)
plt.show()
```



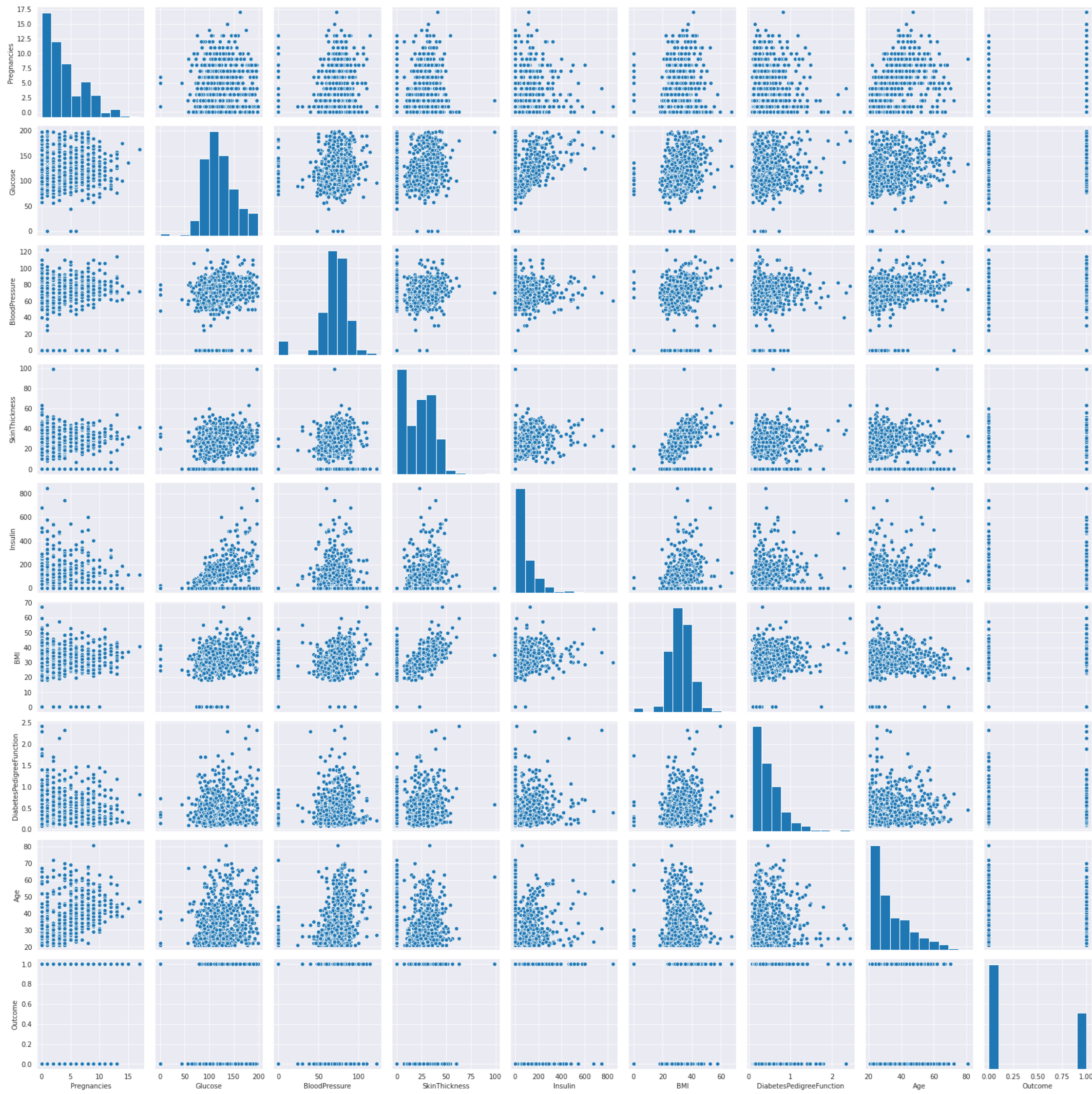

```
[9]: data.corr()
```

```
[9]:                           Pregnancies   Glucose  BloodPressure  SkinThickness  \
     Pregnancies                  1.000000  0.129459       0.141282      -0.081672
     Glucose                      0.129459  1.000000       0.152590       0.057328
     BloodPressure                0.141282  0.152590       1.000000       0.207371
     SkinThickness               -0.081672  0.057328       0.207371       1.000000
     Insulin                     -0.073535  0.331357       0.088933       0.436783
     BMI                          0.017683  0.221071       0.281805       0.392573
     DiabetesPedigreeFunction    -0.033523  0.137337       0.041265       0.183928
     Age                          0.544341  0.263514       0.239528      -0.113970
     Outcome                      0.221898  0.466581       0.065068       0.074752
```

```
                          Insulin       BMI  DiabetesPedigreeFunction  \
Pregnancies             -0.073535  0.017683                 -0.033523
Glucose                  0.331357  0.221071                  0.137337
BloodPressure            0.088933  0.281805                  0.041265
SkinThickness            0.436783  0.392573                  0.183928
Insulin                  1.000000  0.197859                  0.185071
BMI                      0.197859  1.000000                  0.140647
DiabetesPedigreeFunction 0.185071  0.140647                  1.000000
Age                     -0.042163  0.036242                  0.033561
Outcome                  0.130548  0.292695                  0.173844

                              Age   Outcome
Pregnancies              0.544341  0.221898
Glucose                  0.263514  0.466581
BloodPressure            0.239528  0.065068
SkinThickness           -0.113970  0.074752
Insulin                 -0.042163  0.130548
BMI                      0.036242  0.292695
DiabetesPedigreeFunction 0.033561  0.173844
Age                      1.000000  0.238356
Outcome                  0.238356  1.000000
```

[10]:

```
#Using Scatter/pair plot relationship between variables
sns.set_style('darkgrid')
sns.pairplot(data)
plt.show()
```




```
[11]: data.Outcome.value_counts()
```

```
[11]: 0    500
      1    268
      Name: Outcome, dtype: int64
```

```
[12]: for columnName in data.iteritems():
          print('Column Name : ', columnName)
```

```
Column Name :  ('Pregnancies', 0       6
1       1
2       8
3       1
```

```
4       0
       ..
763    10
764     2
765     5
766     1
767     1
Name: Pregnancies, Length: 768, dtype: int64)
Colunm Name :  ('Glucose', 0      148
1       85
2      183
3       89
4      137
      …
763    101
764    122
765    121
766    126
767     93
Name: Glucose, Length: 768, dtype: int64)
Colunm Name :  ('BloodPressure', 0      72
1      66
2      64
3      66
4      40
       ..
763    76
764    70
765    72
766    60
767    70
Name: BloodPressure, Length: 768, dtype: int64)
Colunm Name :  ('SkinThickness', 0      35
1      29
2       0
3      23
4      35
       ..
763    48
764    27
765    23
766     0
767    31
Name: SkinThickness, Length: 768, dtype: int64)
Colunm Name :  ('Insulin', 0        0
1        0
2        0
3       94
```

```
4      168
      …
763    180
764      0
765    112
766      0
767      0
Name: Insulin, Length: 768, dtype: int64)
Colunm Name :  ('BMI', 0      33.6
1      26.6
2      23.3
3      28.1
4      43.1
       …
763    32.9
764    36.8
765    26.2
766    30.1
767    30.4
Name: BMI, Length: 768, dtype: float64)
Colunm Name :  ('DiabetesPedigreeFunction', 0      0.627
1      0.351
2      0.672
3      0.167
4      2.288
       …
763    0.171
764    0.340
765    0.245
766    0.349
767    0.315
Name: DiabetesPedigreeFunction, Length: 768, dtype: float64)
Colunm Name :  ('Age', 0      50
1      31
2      32
3      21
4      33
       ..
763    63
764    27
765    30
766    47
767    23
Name: Age, Length: 768, dtype: int64)
Colunm Name :  ('Outcome', 0      1
1      0
2      1
3      0
```

```
4      1
      ..
763    0
764    0
765    0
766    1
767    0
Name: Outcome, Length: 768, dtype: int64)
```

[13]:
```
x=data.columns
for i in x:
    print(data[i].value_counts())
```

```
1     135
0     111
2     103
3      75
4      68
5      57
6      50
7      45
8      38
9      28
10     24
11     11
13     10
12      9
14      2
15      1
17      1
Name: Pregnancies, dtype: int64
100    17
99     17
129    14
125    14
111    14
       ..
177     1
172     1
169     1
160     1
199     1
Name: Glucose, Length: 136, dtype: int64
70     57
74     52
68     45
78     45
72     44
```

```
64     43
80     40
76     39
60     37
0      35
62     34
66     30
82     30
88     25
84     23
90     22
86     21
58     21
50     13
56     12
52     11
54     11
92      8
75      8
65      7
94      6
85      6
48      5
44      4
96      4
110     3
100     3
98      3
106     3
108     2
104     2
30      2
55      2
46      2
40      1
38      1
24      1
95      1
61      1
102     1
114     1
122     1
Name: BloodPressure, dtype: int64
0     227
32     31
30     27
27     23
23     22
```

```
33      20
18      20
28      20
31      19
39      18
19      18
29      17
37      16
26      16
22      16
40      16
25      16
35      15
41      15
36      14
15      14
17      14
20      13
24      12
42      11
13      11
21      10
34       8
46       8
38       7
12       7
14       6
16       6
11       6
43       6
45       6
10       5
44       5
48       4
47       4
50       3
49       3
54       2
52       2
7        2
8        2
60       1
56       1
63       1
51       1
99       1
Name: SkinThickness, dtype: int64
0      374
```

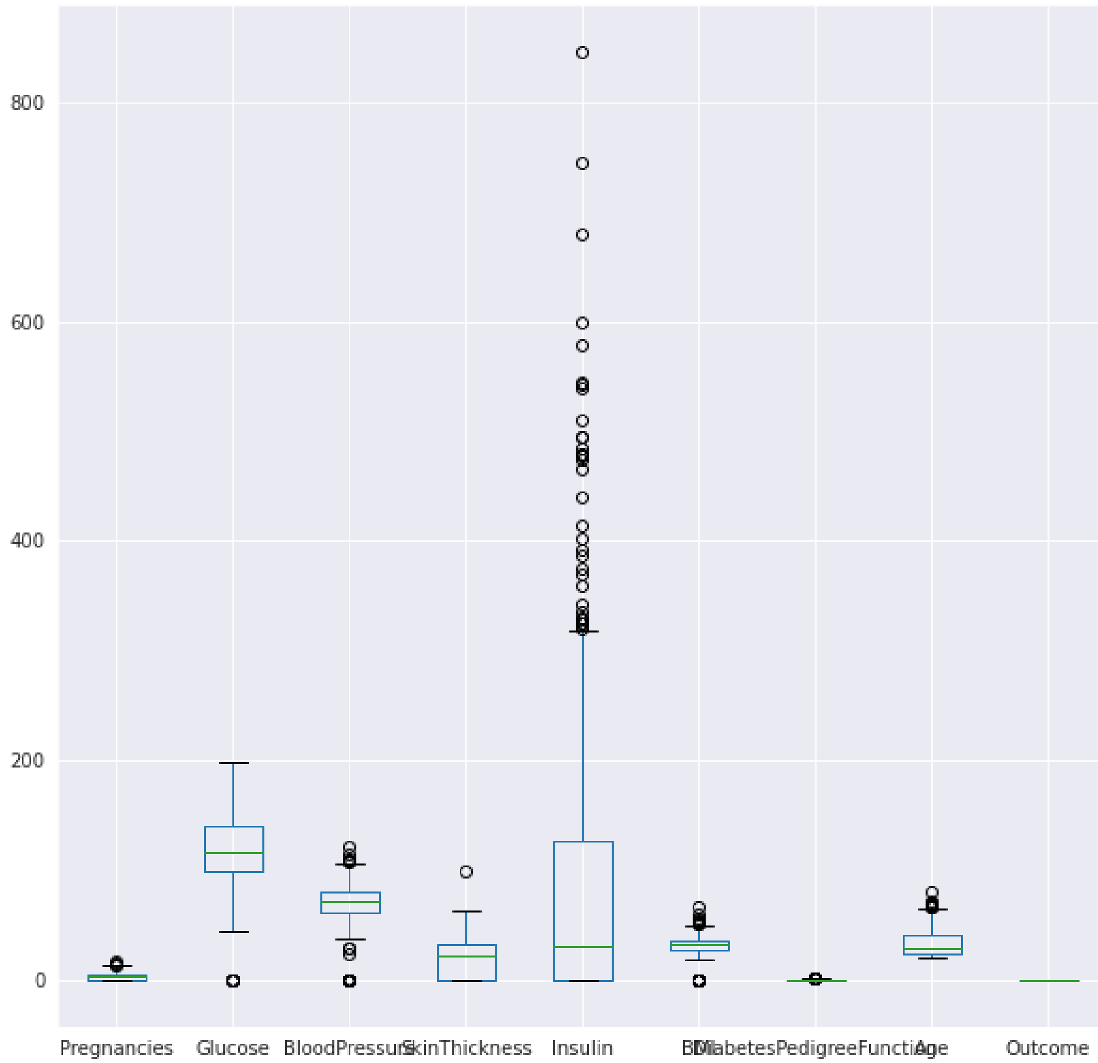
```
105     11
140      9
130      9
120      8
      …
271      1
270      1
108      1
112      1
846      1
Name: Insulin, Length: 186, dtype: int64
32.0    13
31.6    12
31.2    12
0.0     11
33.3    10
        ..
32.1     1
52.9     1
31.3     1
45.7     1
42.8     1
Name: BMI, Length: 248, dtype: int64
0.254    6
0.258    6
0.259    5
0.238    5
0.207    5
        ..
0.886    1
0.804    1
1.251    1
0.382    1
0.375    1
Name: DiabetesPedigreeFunction, Length: 517, dtype: int64
22    72
21    63
25    48
24    46
23    38
28    35
26    33
27    32
29    29
31    24
41    22
30    21
37    19
```

```
42    18
33    17
32    16
36    16
38    16
45    15
34    14
40    13
43    13
46    13
39    12
35    10
50     8
44     8
51     8
52     8
58     7
47     6
54     6
57     5
60     5
48     5
49     5
53     5
55     4
62     4
63     4
66     4
56     3
59     3
65     3
67     3
61     2
69     2
72     1
64     1
68     1
70     1
81     1
Name: Age, dtype: int64
0    500
1    268
Name: Outcome, dtype: int64
```

from the above ,outcome has binary values and its Dependent variable

[14]:
```
#Checking Outliers
plt.figure(figsize=(10,10))
```

```
data.boxplot()
plt.show()
```



#TASK -1 On the columns Glucose,BloodPressure,SkinThickness, Insulin,BMI have value of zero does not make sense and thus indicates missing value and replacing it mean of that Column.

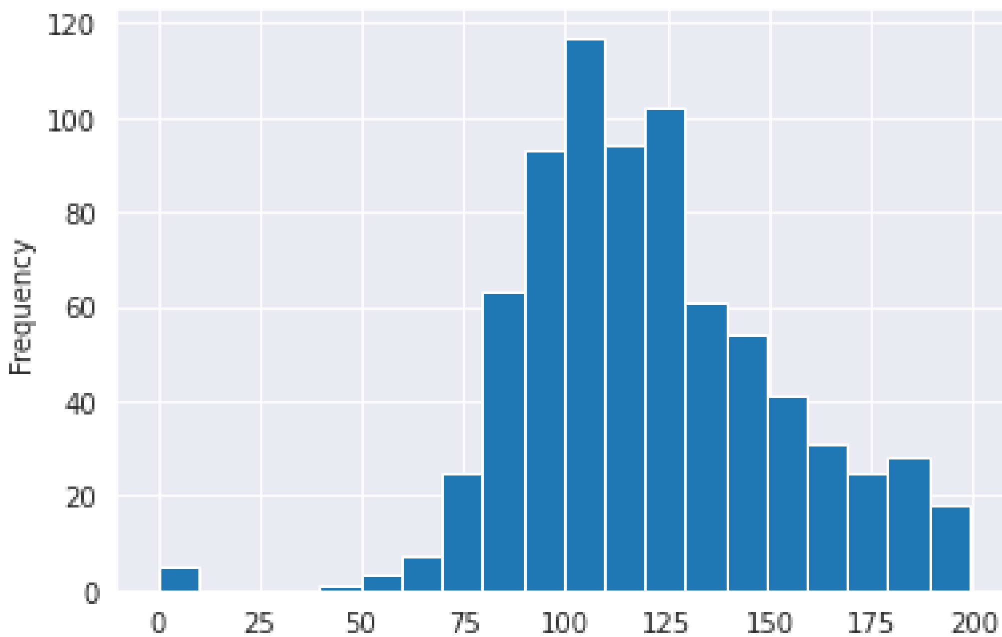
[15]:
```
#Glucose with zero value
data[data['Glucose']==0]
```

[15]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	\
75	1	0	48	20	0	24.7	
182	1	0	74	20	23	27.7	
342	1	0	68	35	0	32.0	
349	5	0	80	32	0	41.0	

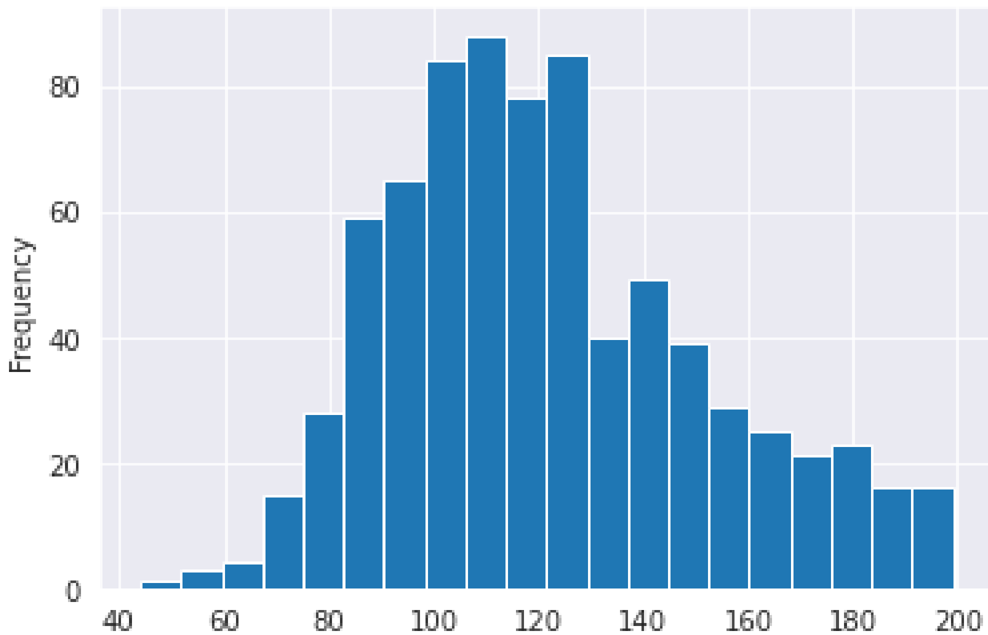
```
502             6         0               68               41          0  39.0

     DiabetesPedigreeFunction  Age  Outcome
75                      0.140   22        0
182                     0.299   21        0
342                     0.389   22        0
349                     0.346   37        1
502                     0.727   41        1
```

[16]:
```
sns.set_style('darkgrid')
data['Glucose'].plot.hist(bins=20)
plt.show()
```



[17]:
```
data['Glucose']=data['Glucose'].replace(0,data['Glucose'].mean())
```

[18]:
```
#after replacing zero  value with mean
sns.set_style('darkgrid')
data['Glucose'].plot.hist(bins=20)
plt.show()
```



[19]:
```
#BloodPressure with zero value
data[data['BloodPressure']==0]
```

[19]:

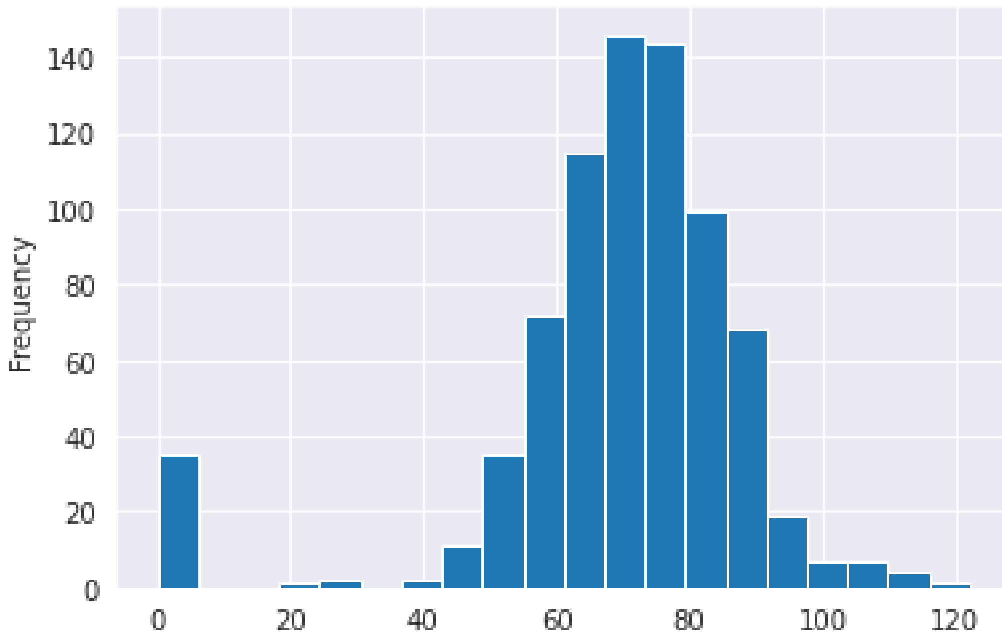
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	\
7	10	115.0	0	0	0	35.3	
15	7	100.0	0	0	0	30.0	
49	7	105.0	0	0	0	0.0	
60	2	84.0	0	0	0	0.0	
78	0	131.0	0	0	0	43.2	
81	2	74.0	0	0	0	0.0	
172	2	87.0	0	23	0	28.9	
193	11	135.0	0	0	0	52.3	
222	7	119.0	0	0	0	25.2	
261	3	141.0	0	0	0	30.0	
266	0	138.0	0	0	0	36.3	
269	2	146.0	0	0	0	27.5	
300	0	167.0	0	0	0	32.3	
332	1	180.0	0	0	0	43.3	
336	0	117.0	0	0	0	33.8	
347	3	116.0	0	0	0	23.5	
357	13	129.0	0	30	0	39.9	
426	0	94.0	0	0	0	0.0	
430	2	99.0	0	0	0	22.2	
435	0	141.0	0	0	0	42.4	
453	2	119.0	0	0	0	19.6	
468	8	120.0	0	0	0	30.0	

484	0	145.0	0	0	0	44.2
494	3	80.0	0	0	0	0.0
522	6	114.0	0	0	0	0.0
533	6	91.0	0	0	0	29.8
535	4	132.0	0	0	0	32.9
589	0	73.0	0	0	0	21.1
601	6	96.0	0	0	0	23.7
604	4	183.0	0	0	0	28.4
619	0	119.0	0	0	0	32.4
643	4	90.0	0	0	0	28.0
697	0	99.0	0	0	0	25.0
703	2	129.0	0	0	0	38.5
706	10	115.0	0	0	0	0.0

	DiabetesPedigreeFunction	Age	Outcome
7	0.134	29	0
15	0.484	32	1
49	0.305	24	0
60	0.304	21	0
78	0.270	26	1
81	0.102	22	0
172	0.773	25	0
193	0.578	40	1
222	0.209	37	0
261	0.761	27	1
266	0.933	25	1
269	0.240	28	1
300	0.839	30	1
332	0.282	41	1
336	0.932	44	0
347	0.187	23	0
357	0.569	44	1
426	0.256	25	0
430	0.108	23	0
435	0.205	29	1
453	0.832	72	0
468	0.183	38	1
484	0.630	31	1
494	0.174	22	0
522	0.189	26	0
533	0.501	31	0
535	0.302	23	1
589	0.342	25	0
601	0.190	28	0
604	0.212	36	1
619	0.141	24	1
643	0.610	31	0

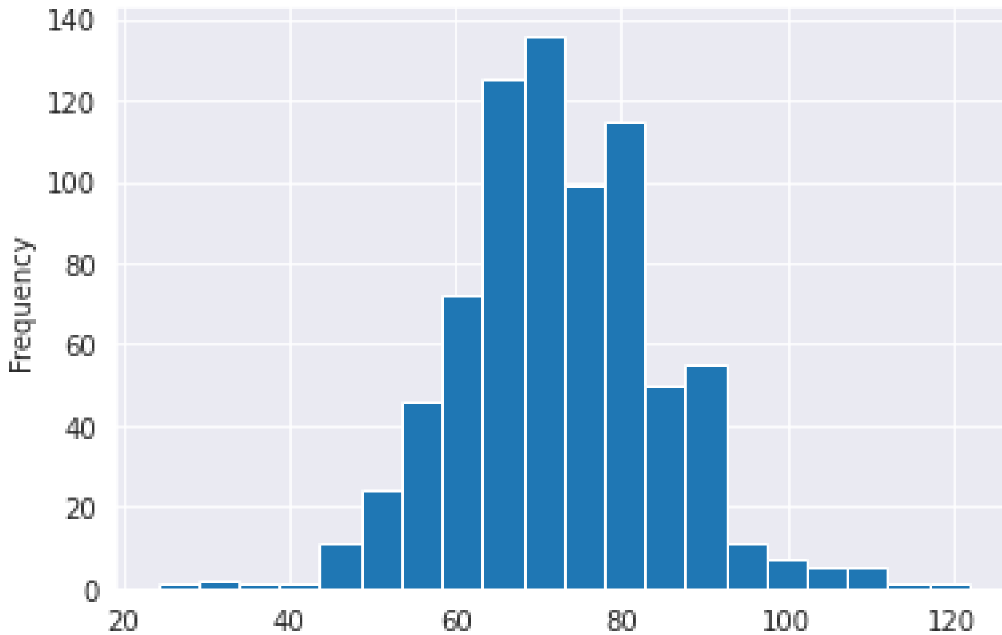
```
697                         0.253   22          0
703                         0.304   41          0
706                         0.261   30          1
```

[20]:
```
sns.set_style('darkgrid')
data['BloodPressure'].plot.hist(bins=20)

plt.show()
```



[21]:
```
data['BloodPressure']=data['BloodPressure'].replace(0,data['BloodPressure'].
 ↪mean())
```

[22]:
```
#after replacing zero  value with mean
sns.set_style('darkgrid')
data['BloodPressure'].plot.hist(bins=20)
plt.show()
```

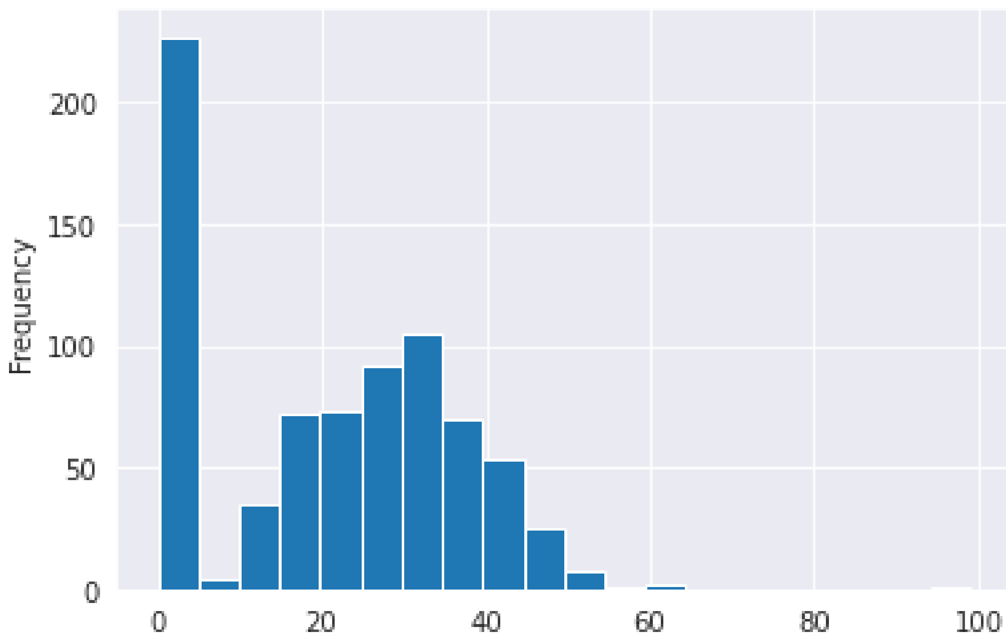


[23]:
```python
#SkinThickness with zero value
data[data['SkinThickness']==0]
```

[23]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
2              8    183.0      64.000000              0        0  23.3
5              5    116.0      74.000000              0        0  25.6
7             10    115.0      69.105469              0        0  35.3
9              8    125.0      96.000000              0        0   0.0
10             4    110.0      92.000000              0        0  37.6
..           …        …            …            …      …    …
757            0    123.0      72.000000              0        0  36.3
758            1    106.0      76.000000              0        0  37.5
759            6    190.0      92.000000              0        0  35.5
762            9     89.0      62.000000              0        0  22.5
766            1    126.0      60.000000              0        0  30.1

     DiabetesPedigreeFunction  Age  Outcome
2                       0.672   32        1
5                       0.201   30        0
7                       0.134   29        0
9                       0.232   54        1
10                      0.191   30        0
..                        …  …      …
757                     0.258   52        1
758                     0.197   26        0
759                     0.278   66        1
```

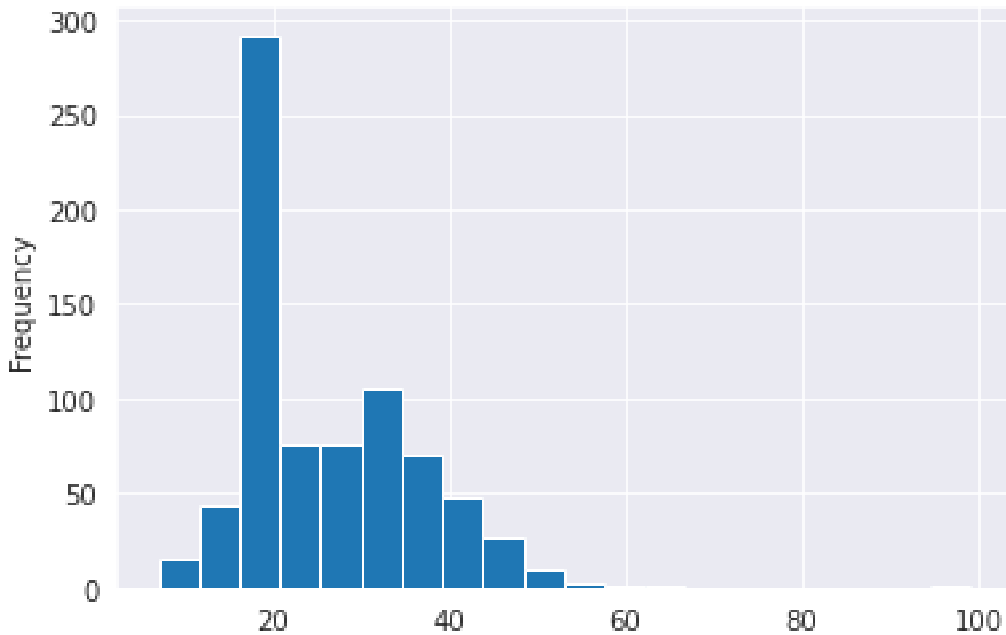
```
762                        0.142   33         0
766                        0.349   47         1

[227 rows x 9 columns]
```

[24]:
```
sns.set_style('darkgrid')
data['SkinThickness'].plot.hist(bins=20)
plt.show()
```



[25]:
```
data['SkinThickness']=data['SkinThickness'].replace(0,data['SkinThickness'].
 ↪mean())
```

[26]:
```
#after replacing zero  value with mean
sns.set_style('darkgrid')
data['SkinThickness'].plot.hist(bins=20)
plt.show()
```



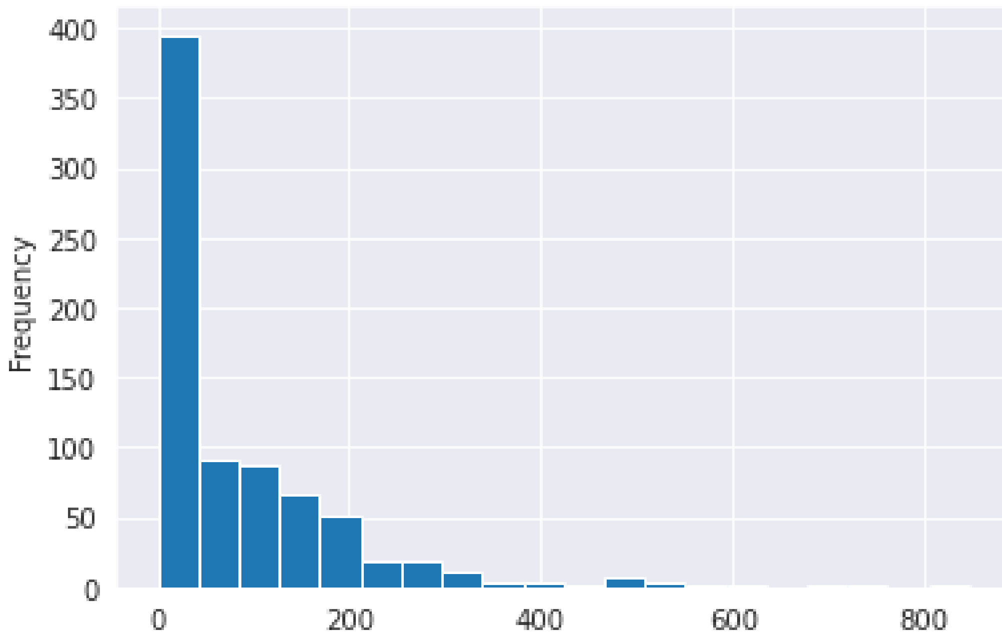
[27]:
```
#Insulin with zero value
data[data['Insulin']==0]
```

[27]:
```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              6    148.0      72.000000      35.000000        0  33.6
1              1     85.0      66.000000      29.000000        0  26.6
2              8    183.0      64.000000      20.536458        0  23.3
5              5    116.0      74.000000      20.536458        0  25.6
7             10    115.0      69.105469      20.536458        0  35.3
..           …       …            …              …        …      …
761            9    170.0      74.000000      31.000000        0  44.0
762            9     89.0      62.000000      20.536458        0  22.5
764            2    122.0      70.000000      27.000000        0  36.8
766            1    126.0      60.000000      20.536458        0  30.1
767            1     93.0      70.000000      31.000000        0  30.4

     DiabetesPedigreeFunction  Age  Outcome
0                       0.627   50        1
1                       0.351   31        0
2                       0.672   32        1
5                       0.201   30        0
7                       0.134   29        0
..                        …   …       …
761                     0.403   43        1
762                     0.142   33        0
764                     0.340   27        0
```

```
766                        0.349   47         1
767                        0.315   23         0

[374 rows x 9 columns]
```

[28]:

```
sns.set_style('darkgrid')
data['Insulin'].plot.hist(bins=20)
plt.show()
```

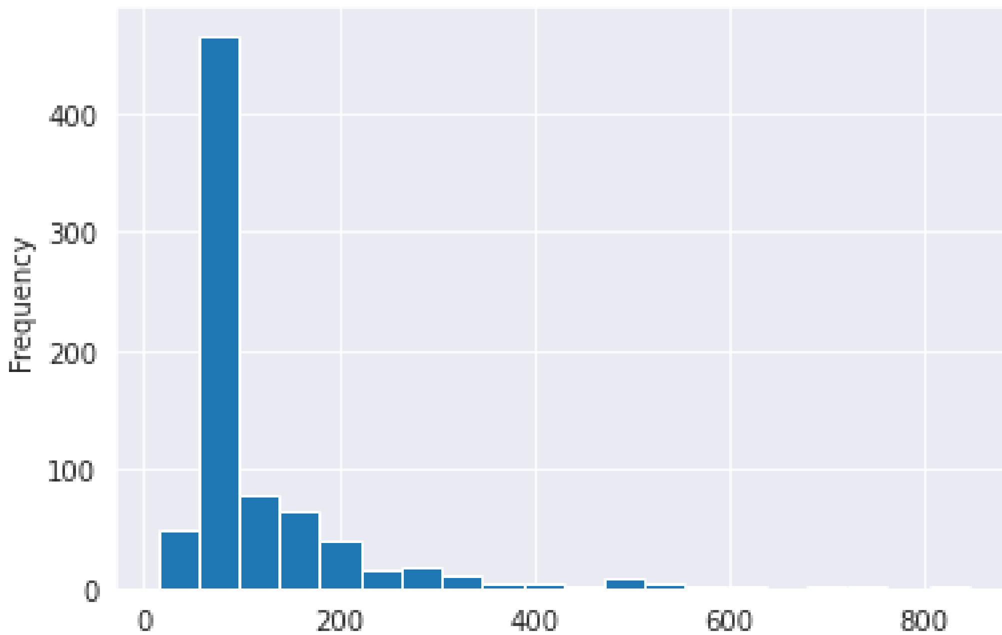


[29]:

```
data['Insulin']=data['Insulin'].replace(0,data['Insulin'].mean())
```

[30]:

```
#after replacing zero  value with mean
sns.set_style('darkgrid')
data['Insulin'].plot.hist(bins=20)
plt.show()
```



[31]:
```
#BMI with zero value
data[data['BMI']==0]
```

[31]:

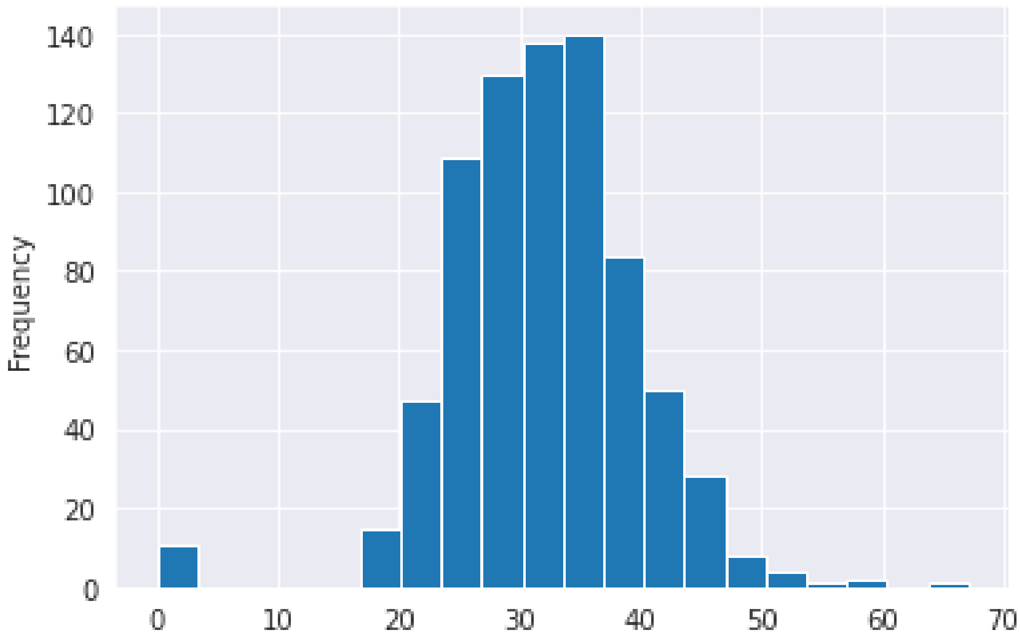
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	\
9	8	125.0	96.000000	20.536458	79.799479	0.0	
49	7	105.0	69.105469	20.536458	79.799479	0.0	
60	2	84.0	69.105469	20.536458	79.799479	0.0	
81	2	74.0	69.105469	20.536458	79.799479	0.0	
145	0	102.0	75.000000	23.000000	79.799479	0.0	
371	0	118.0	64.000000	23.000000	89.000000	0.0	
426	0	94.0	69.105469	20.536458	79.799479	0.0	
494	3	80.0	69.105469	20.536458	79.799479	0.0	
522	6	114.0	69.105469	20.536458	79.799479	0.0	
684	5	136.0	82.000000	20.536458	79.799479	0.0	
706	10	115.0	69.105469	20.536458	79.799479	0.0	

	DiabetesPedigreeFunction	Age	Outcome
9	0.232	54	1
49	0.305	24	0
60	0.304	21	0
81	0.102	22	0
145	0.572	21	0
371	1.731	21	0
426	0.256	25	0
494	0.174	22	0
522	0.189	26	0

684	0.640	69	0
706	0.261	30	1

[32]:

```
sns.set_style('darkgrid')
data['BMI'].plot.hist(bins=20)
plt.show()
```

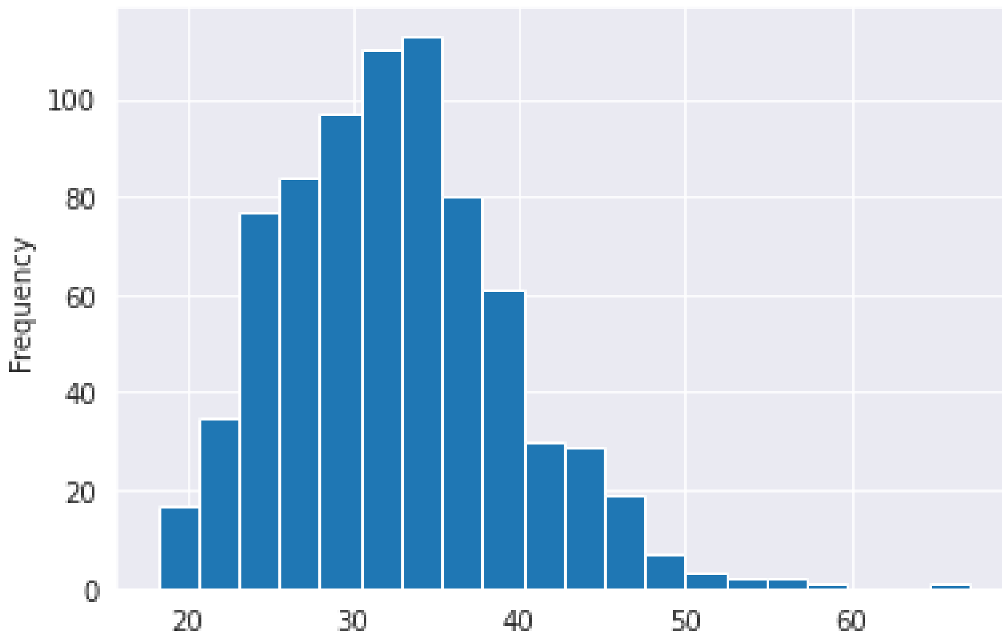


[33]:

```
data['BMI']=data['BMI'].replace(0,data['BMI'].mean())
```

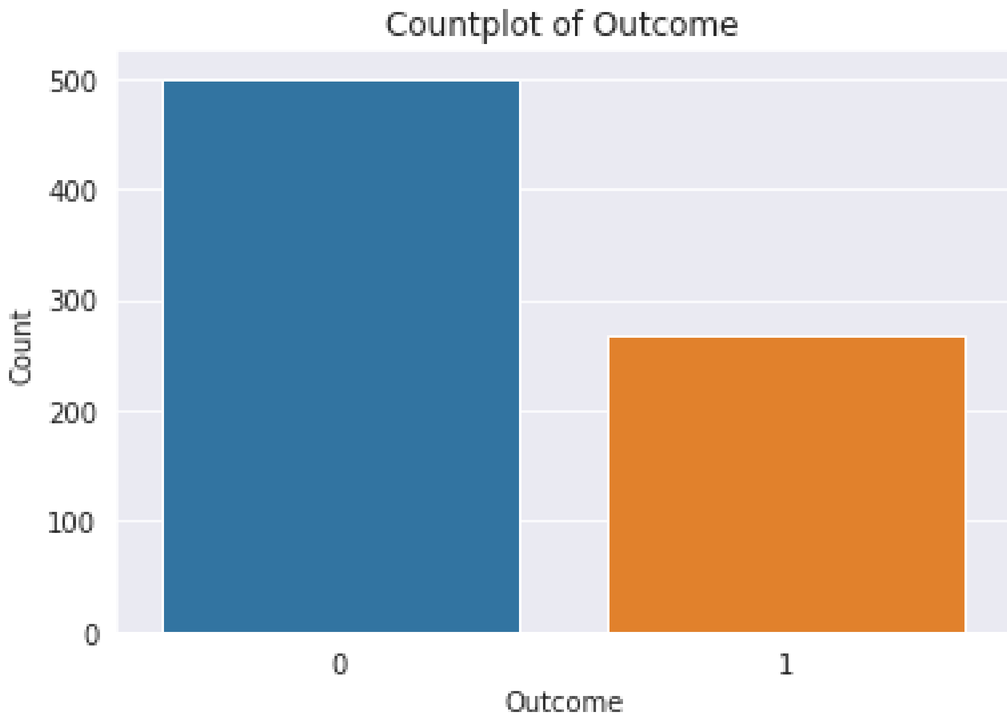
[34]:

```
#after replacing zero  value with mean
sns.set_style('darkgrid')
data['BMI'].plot.hist(bins=20)
plt.show()
```

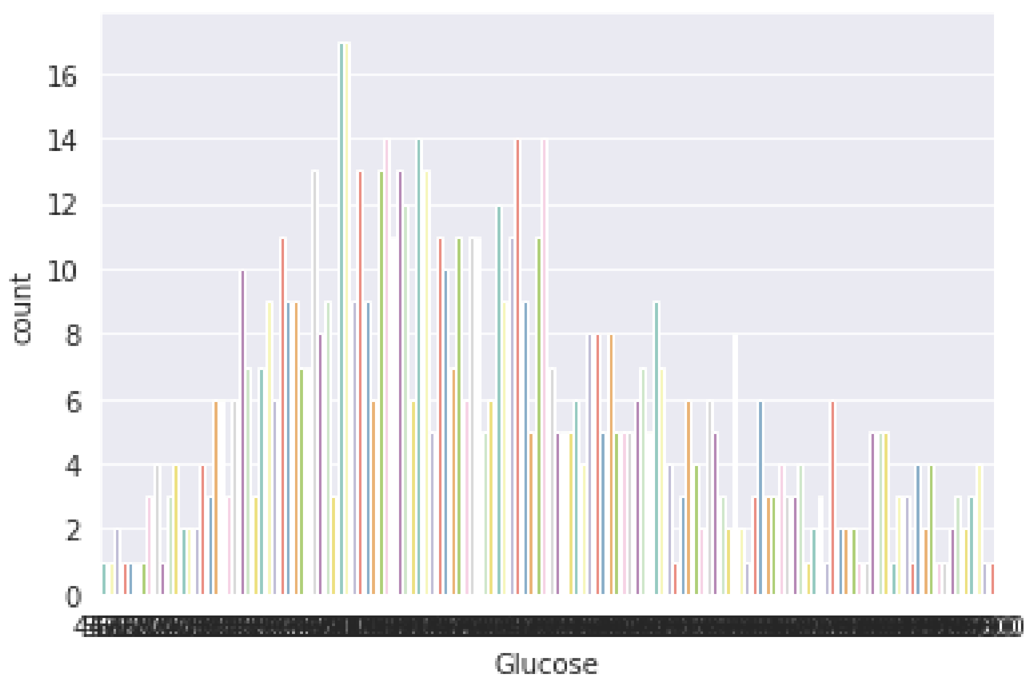


[35]:
```
sns.set_style('darkgrid')
sns.countplot(data['Outcome'])
plt.title("Countplot of Outcome")
plt.xlabel('Outcome')
plt.ylabel("Count")
```

[35]:
```
Text(0, 0.5, 'Count')
```



[36]:
```
sns.set_style(style="darkgrid")
sns.countplot(x="Glucose", data=data, palette="Set3")
plt.show()
```



[37]:
```
data['Glucose'].value_counts()
```

[37]:
```
100.0    17
99.0     17
125.0    14
106.0    14
111.0    14
         ..
182.0     1
169.0     1
160.0     1
62.0      1
149.0     1
Name: Glucose, Length: 136, dtype: int64
```

[38]:
```
data['BloodPressure'].value_counts()
```

[38]:
```
70.000000     57
74.000000     52
68.000000     45
78.000000     45
72.000000     44
64.000000     43
80.000000     40
76.000000     39
60.000000     37
69.105469     35
62.000000     34
66.000000     30
82.000000     30
88.000000     25
84.000000     23
90.000000     22
58.000000     21
86.000000     21
50.000000     13
56.000000     12
52.000000     11
54.000000     11
92.000000      8
75.000000      8
65.000000      7
85.000000      6
94.000000      6
48.000000      5
```

```
96.000000      4
44.000000      4
106.000000     3
100.000000     3
110.000000     3
98.000000      3
30.000000      2
108.000000     2
55.000000      2
46.000000      2
104.000000     2
102.000000     1
95.000000      1
61.000000      1
114.000000     1
24.000000      1
38.000000      1
40.000000      1
122.000000     1
Name: BloodPressure, dtype: int64
```

[39]:
```python
data['SkinThickness'].value_counts()
```

[39]:
```
20.536458    227
32.000000     31
30.000000     27
27.000000     23
23.000000     22
33.000000     20
18.000000     20
28.000000     20
31.000000     19
19.000000     18
39.000000     18
29.000000     17
40.000000     16
37.000000     16
25.000000     16
22.000000     16
26.000000     16
41.000000     15
35.000000     15
36.000000     14
17.000000     14
15.000000     14
20.000000     13
24.000000     12
```

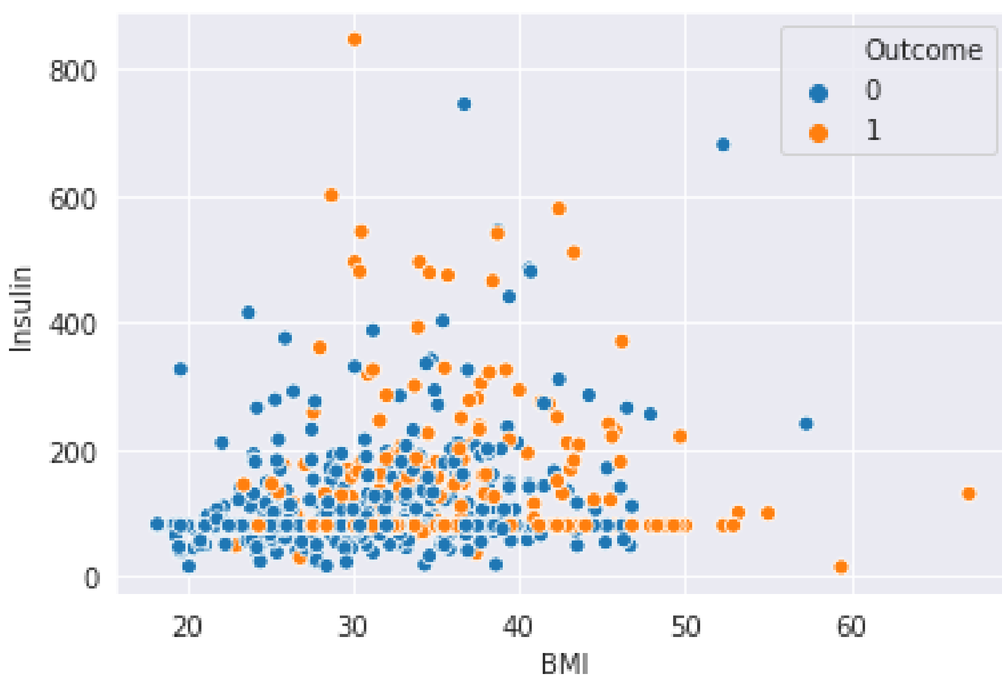
```
42.000000     11
13.000000     11
21.000000     10
34.000000      8
46.000000      8
38.000000      7
12.000000      7
11.000000      6
14.000000      6
43.000000      6
16.000000      6
45.000000      6
10.000000      5
44.000000      5
47.000000      4
48.000000      4
50.000000      3
49.000000      3
7.000000       2
52.000000      2
8.000000       2
54.000000      2
51.000000      1
99.000000      1
60.000000      1
56.000000      1
63.000000      1
Name: SkinThickness, dtype: int64
```

[40]:
```
data['Insulin'].value_counts()
```

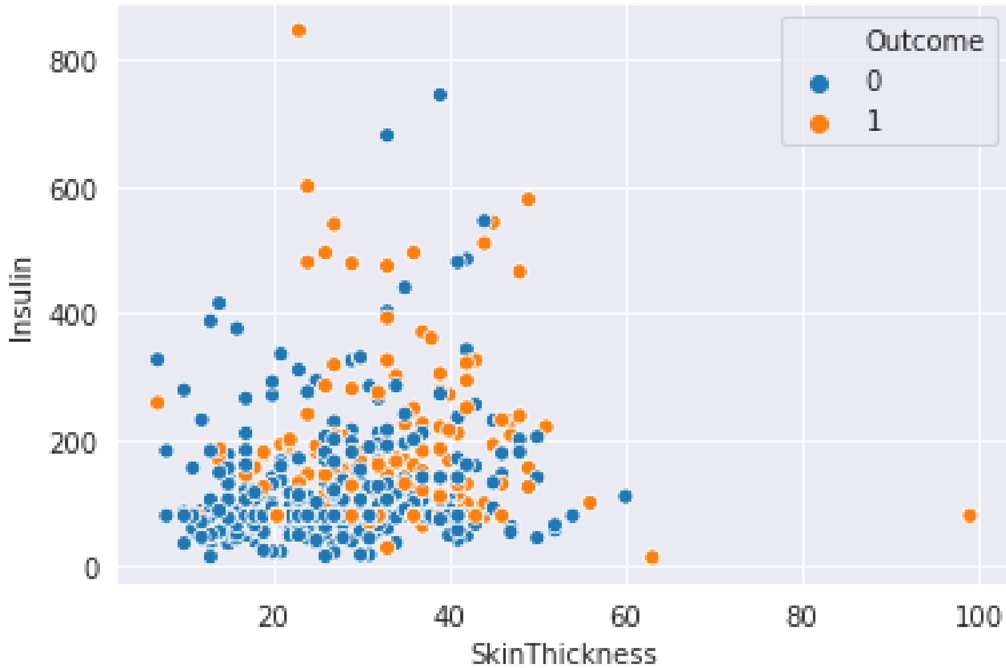
[40]:
```
79.799479     374
105.000000     11
130.000000      9
140.000000      9
120.000000      8
             …
15.000000       1
272.000000      1
41.000000       1
25.000000       1
59.000000       1
Name: Insulin, Length: 186, dtype: int64
```

[41]:
```
glu =sns.scatterplot(x= "Glucose" ,y= "BloodPressure", hue="Outcome", data=data)
```


```
[42]: bmi =sns.scatterplot(x= "BMI" ,y= "Insulin",hue="Outcome",data=data);
```



[43]:
```
st =sns.scatterplot(x= "SkinThickness" ,y= "Insulin",hue="Outcome",data=data)
```



2.2 Model Building

2.3 First Way to detect best Model from Different Model

[44]:
```
#Different Model Techniques

#LogisticRegression
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression()

#Applying Decission Tree Classifier
from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier(criterion='gini',max_depth=7)

#Applying Ensemble Technique-Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators=7)

#Applying K-NN
from math import sqrt
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=7,metric='minkowski',p = 2)
```

```
#Support Vector Classifier
from sklearn.svm import SVC
sv = SVC(kernel='rbf',gamma='auto')
```

[45]:
```
#Defining Features n Label
X = data.drop("Outcome",axis=1)
y = data['Outcome']
print(X.shape)
print(y.shape)
```

```
(768, 8)
(768,)
```

[46]:
```
#Train test split
from sklearn.model_selection import cross_val_score
```

[47]:
```
#LogisticRegression
cross_val_score(lr,X,y)
```

[47]:
```
array([0.74675325, 0.77922078, 0.74025974, 0.82352941, 0.75816993])
```

[48]:
```
#Applying DecissionTreeClassifier
cross_val_score(dtc,X,y)
```

[48]:
```
array([0.68831169, 0.72077922, 0.65584416, 0.76470588, 0.73856209])
```

[49]:
```
#Applying Ensemble Technique-RandomForestClassifier
cross_val_score(rf,X,y)
```

[49]:
```
array([0.7012987 , 0.71428571, 0.74675325, 0.79084967, 0.73202614])
```

[50]:
```
#Applying K-NN
cross_val_score(knn,X,y)
```

[50]:
```
array([0.73376623, 0.67532468, 0.74675325, 0.79084967, 0.75163399])
```

[51]:
```
#Applying SupportVectorClassifier
cross_val_score(sv,X,y)
```

[51]:
```
array([0.64935065, 0.64935065, 0.64935065, 0.65359477, 0.65359477])
```

Logistic Regression is best Model ,RFC will be second and with hyper parameter tunning performance will increase.

3 Second Option -One by one Model Analysis

[52]:
```
#Train test split
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=.
↪25,random_state=50 )
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(576, 8)
(192, 8)
(576,)
(192,)
```

4 LogisticRegression

[53]:
```
#Creating Model

from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
#fit the Train data into Model
lr.fit(X_train,y_train)
```

[53]:
```
LogisticRegression()
```

[54]:
```
#Score at Test data
print(lr.score(X_test,y_test))
```

```
0.7552083333333334
```

[55]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y,lr.predict(X))
cm
```

[55]:
```
array([[448,  52],
       [120, 148]])
```

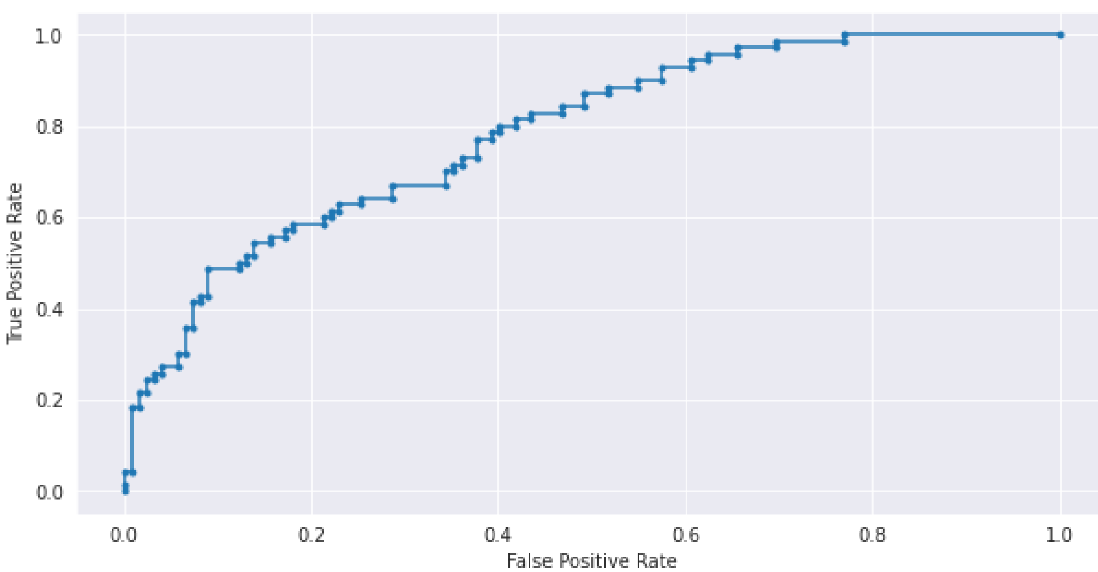
[56]:
```
from sklearn.metrics import classification_report
print(classification_report(y,lr.predict(X)))
```

```
              precision    recall  f1-score   support

           0       0.79      0.90      0.84       500
           1       0.74      0.55      0.63       268
```

```
    accuracy                           0.78       768
   macro avg       0.76      0.72      0.74       768
weighted avg       0.77      0.78      0.77       768
```

[57]:
```
y_predict=lr.decision_function(X_test)
```

[58]:
```
from sklearn.metrics import roc_curve,auc
from sklearn.metrics import roc_auc_score

fpr, tpr, thresholds = roc_curve(y_test, y_predict)
auc=auc(fpr,tpr)
plt.figure(figsize=(10,5))
plt.plot(fpr,tpr,marker='.',label='AUC: %.3f' % auc)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()

# calculate AUC
auc = roc_auc_score(y_test, y_predict)
print('AUC: %.3f' % auc)
```




```
AUC: 0.785
```

5 Applying DecissionTreeClassifier

[59]:
```
from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier(criterion='gini')
dtc.fit(X_train,y_train)
```

[59]:
```
DecisionTreeClassifier()
```

[60]:
```
dtc.score(X_test,y_test)
```

[60]:
```
0.6822916666666666
```

[61]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y,dtc.predict(X))
cm
```

[61]:
```
array([[467,  33],
       [ 28, 240]])
```

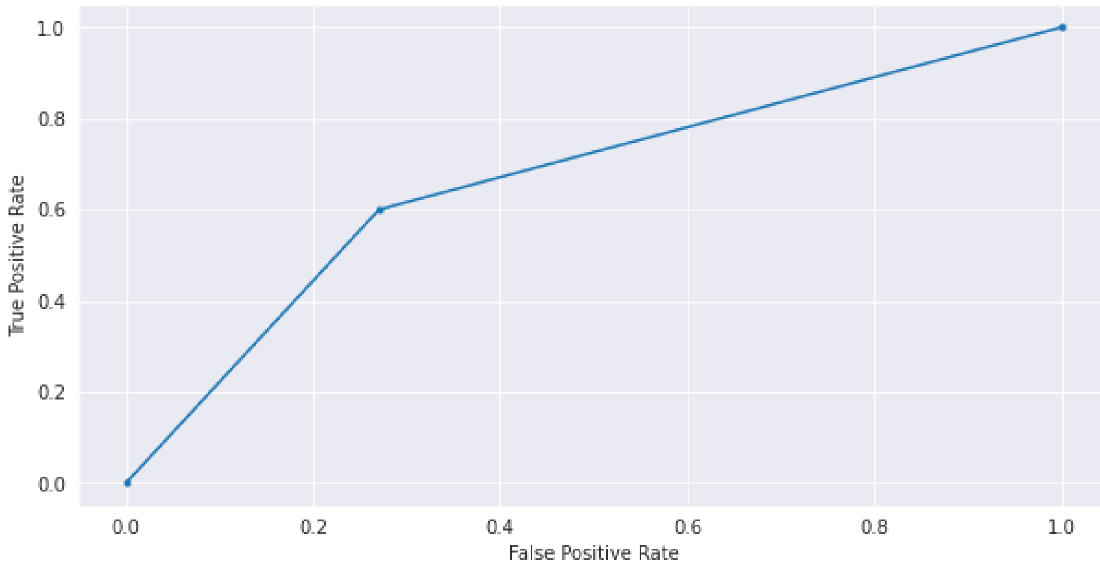
[62]:
```
from sklearn.metrics import classification_report
print(classification_report(y,dtc.predict(X)))
```

```
              precision    recall  f1-score   support

           0       0.94      0.93      0.94       500
           1       0.88      0.90      0.89       268

    accuracy                           0.92       768
   macro avg       0.91      0.91      0.91       768
weighted avg       0.92      0.92      0.92       768
```

[63]:
```
y_predict=dtc.predict_proba(X_test)
y_predict=y_predict[:, 1]
```

[64]:
```
from sklearn.metrics import roc_curve,auc
from sklearn.metrics import roc_auc_score

fpr, tpr, thresholds = roc_curve(y_test, y_predict)
auc=auc(fpr,tpr)
plt.figure(figsize=(10,5))
plt.plot(fpr,tpr,marker='.',label='AUC: %.3f' % auc)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()

# calculate AUC
```

```
auc = roc_auc_score(y_test, y_predict)
print('AUC: %.3f' % auc)
```




```
AUC: 0.665
```

[ ]:

```

```

6 Applying Ensemble Technique-RandomForestClassifier

[65]:

```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators=11)
rf.fit(X_train,y_train)
```

[65]:

```
RandomForestClassifier(n_estimators=11)
```

[66]:

```
rf.score(X_test,y_test)
```

[66]:

```
0.703125
```

[67]:

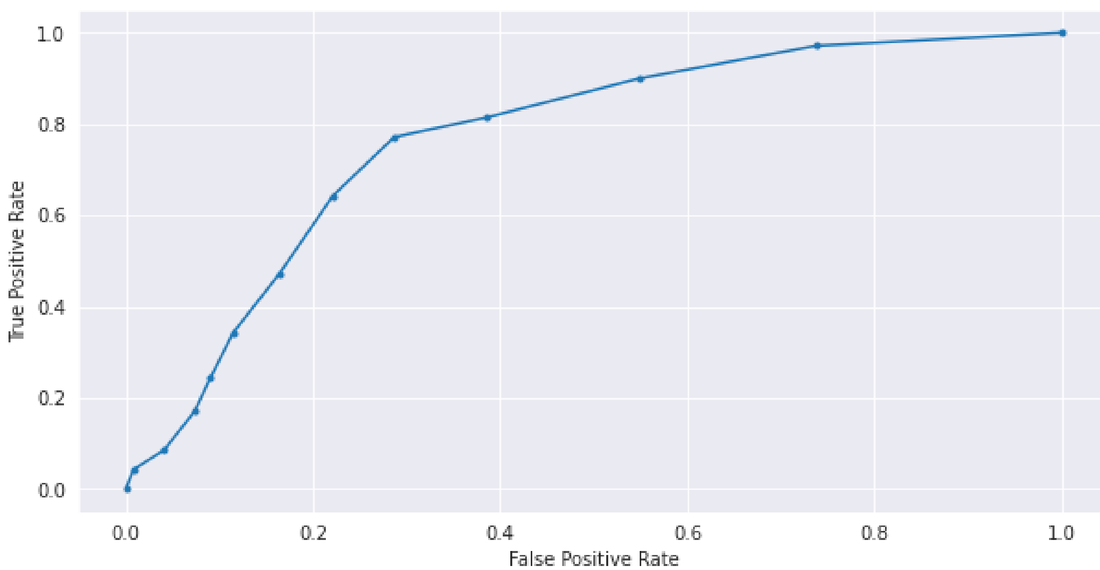
```
from sklearn.metrics import classification_report
print(classification_report(y,rf.predict(X)))
```

```
              precision    recall  f1-score   support

           0       0.92      0.95      0.94       500
           1       0.91      0.85      0.88       268
```

```
    accuracy                           0.92       768
   macro avg       0.92      0.90      0.91       768
weighted avg       0.92      0.92      0.92       768
```

[68]:
```
y_predict=rf.predict_proba(X_test)
y_predict=y_predict[:, 1]
```

[69]:
```
from sklearn.metrics import roc_curve,auc
from sklearn.metrics import roc_auc_score

fpr, tpr, thresholds = roc_curve(y_test, y_predict)
auc=auc(fpr,tpr)
plt.figure(figsize=(10,5))
plt.plot(fpr,tpr,marker='.',label='AUC: %.3f' % auc)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()

# calculate AUC
auc = roc_auc_score(y_test, y_predict)
print('AUC: %.3f' % auc)
```




```
AUC: 0.769
```

7 Support Vector Classifier

[70]:
```python
from sklearn.svm import SVC
sv = SVC(kernel='rbf',gamma='auto')
sv.fit(X_train,y_train)
```

[70]:
```
SVC(gamma='auto')
```

[71]:
```python
sv.score(X_test,y_test)
```

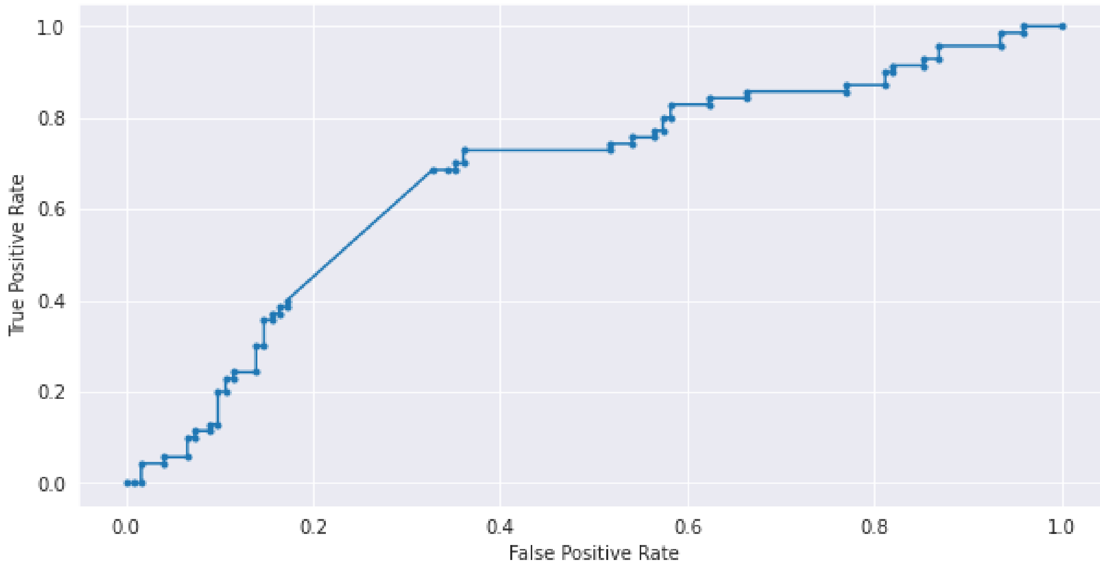
[71]:
```
0.6354166666666666
```

[72]:
```python
from sklearn.metrics import classification_report
print(classification_report(y,sv.predict(X)))
```

```
              precision    recall  f1-score   support

           0       0.88      1.00      0.93       500
           1       1.00      0.74      0.85       268

    accuracy                           0.91       768
   macro avg       0.94      0.87      0.89       768
weighted avg       0.92      0.91      0.90       768
```

[73]:
```python
y_predict=sv.decision_function(X_test)
```

[74]:
```python
from sklearn.metrics import roc_curve,auc
from sklearn.metrics import roc_auc_score

fpr, tpr, thresholds = roc_curve(y_test, y_predict)
auc=auc(fpr,tpr)
plt.figure(figsize=(10,5))
plt.plot(fpr,tpr,marker='.',label='AUC: %.3f' % auc)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()

# calculate AUC
auc = roc_auc_score(y_test, y_predict)
print('AUC: %.3f' % auc)
```



AUC: 0.674

8 Applying K-NN

[75]:
```python
from math import sqrt
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=7,metric='minkowski',p = 2)
knn.fit(X_train,y_train)
```

[75]: KNeighborsClassifier(n_neighbors=7)

[76]:
```python
knn.score(X_test,y_test)
```

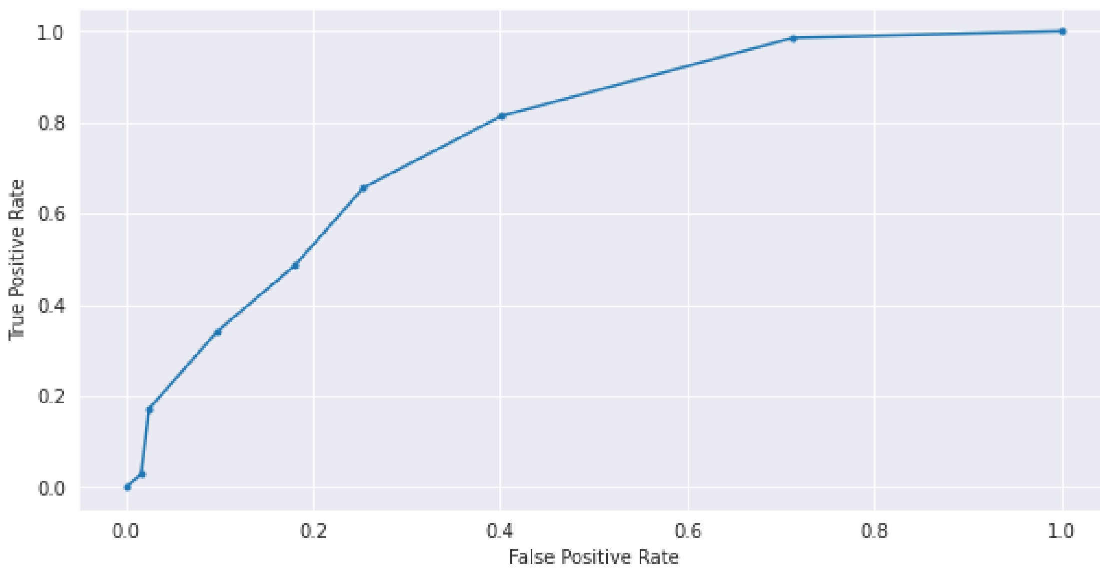
[76]: 0.6979166666666666

[77]:
```python
from sklearn.metrics import classification_report
print(classification_report(y,knn.predict(X)))
```

```
              precision    recall  f1-score   support

           0       0.80      0.86      0.83       500
           1       0.70      0.60      0.64       268

    accuracy                           0.77       768
   macro avg       0.75      0.73      0.74       768
weighted avg       0.76      0.77      0.76       768
```

[78]:
```
y_predict=knn.predict_proba(X_test)
y_predict=y_predict[:, 1]
```

[79]:
```
from sklearn.metrics import roc_curve,auc
from sklearn.metrics import roc_auc_score

fpr, tpr, thresholds = roc_curve(y_test, y_predict)
auc=auc(fpr,tpr)
plt.figure(figsize=(10,5))
plt.plot(fpr,tpr,marker='.',label='AUC: %.3f' % auc)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()

# calculate AUC
auc = roc_auc_score(y_test, y_predict)
print('AUC: %.3f' % auc)
```




```
AUC: 0.770
```

[ ]:
```
Basis of Precision and Recall values,RandomForestClassifier is best Model.
```