meriskills-diabetes

September 21, 2023

0.1 Import libs

[20]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

0.2 load Dataset

[3]:
```
df = pd.read_csv('diabetes.csv')
```

[5]:
```
df
```

[5]:
```
     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
..           …        …            …            …      …     …
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

     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
..                        …   …      …
763                     0.171   63        0
764                     0.340   27        0
765                     0.245   30        0
766                     0.349   47        1
767                     0.315   23        0
```

[768 rows x 9 columns]

0.3 Explore The Dataset

[8]:
```
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
```

[9]:
```
df.describe()
```

[9]:
```
       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
```

[11]:
```
df.isnull().sum()
```

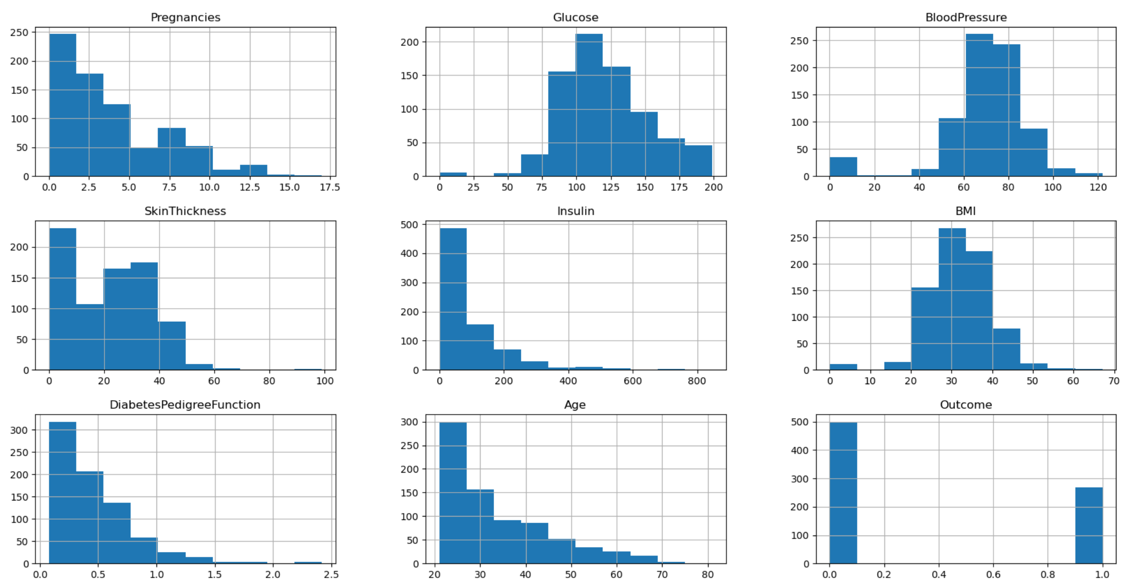
[11]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

[12]:
```python
df.duplicated().sum()
```

[12]: 0

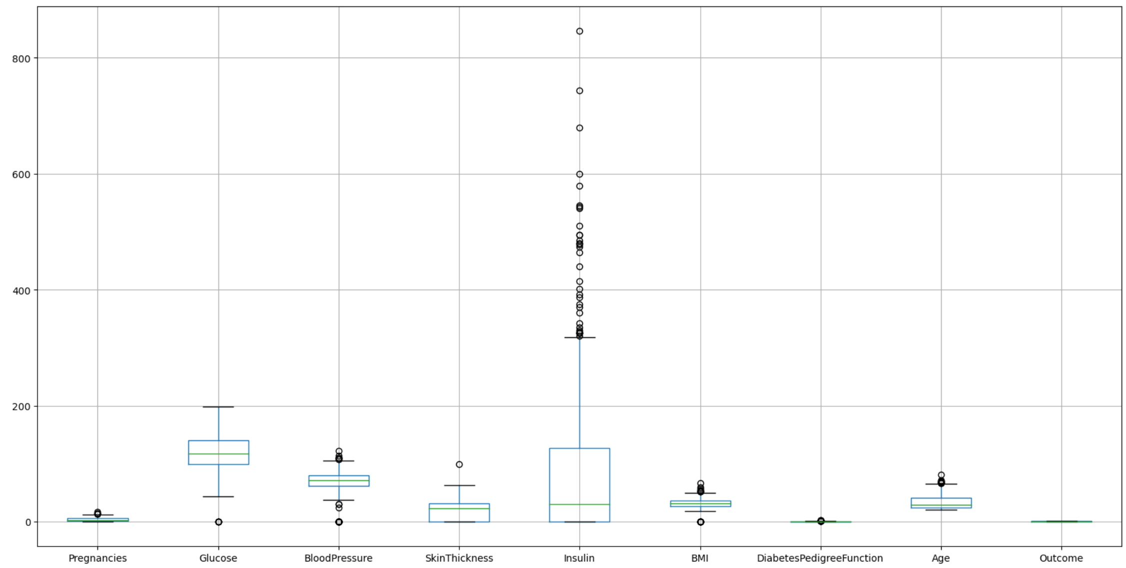
0.3.1 so our data is very clean we will not make a preprocessing on it

[13]:
```python
df.hist(bins = 10, figsize = (20, 10))
plt.show()
```



[15]:
```python
plt.figure(figsize = (20, 10))
df.boxplot()
```

[15]: <AxesSubplot:>



0.3.2 lets work on diabetes factors

[38]:
```
df.corr()
```

[38]:

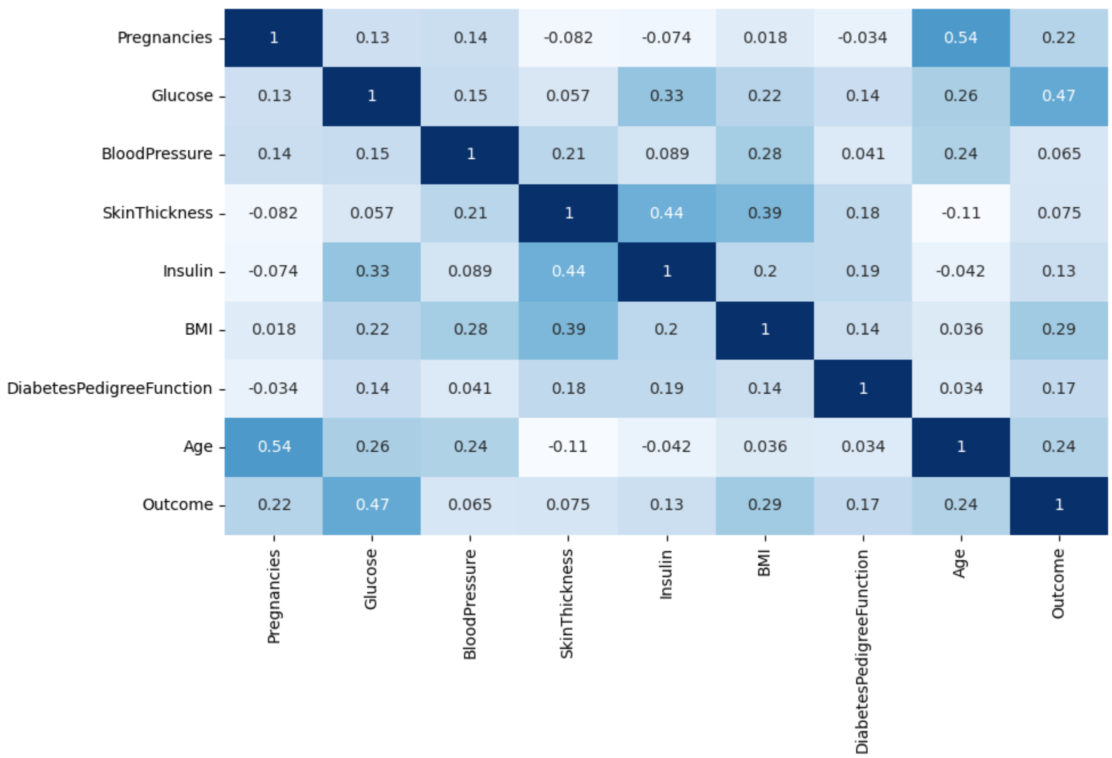
	Pregnancies	Glucose	BloodPressure	SkinThickness	\
Pregnancies	1.000000	0.129459	0.141282	-0.081672	
Glucose	0.129459	1.000000	0.152590	0.057328	
BloodPressure	0.141282	0.152590	1.000000	0.207371	
SkinThickness	-0.081672	0.057328	0.207371	1.000000	
Insulin	-0.073535	0.331357	0.088933	0.436783	
BMI	0.017683	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

[40]:
```
plt.figure(figsize = (10, 6))

sns.heatmap(df.corr(), annot = True, cbar = False, cmap = 'Blues')
plt.show()
```



0.4 Lets get insights from factors

[44]:
```
#split data to only diabetes
di_df = df[df['Outcome'] == 1]
```

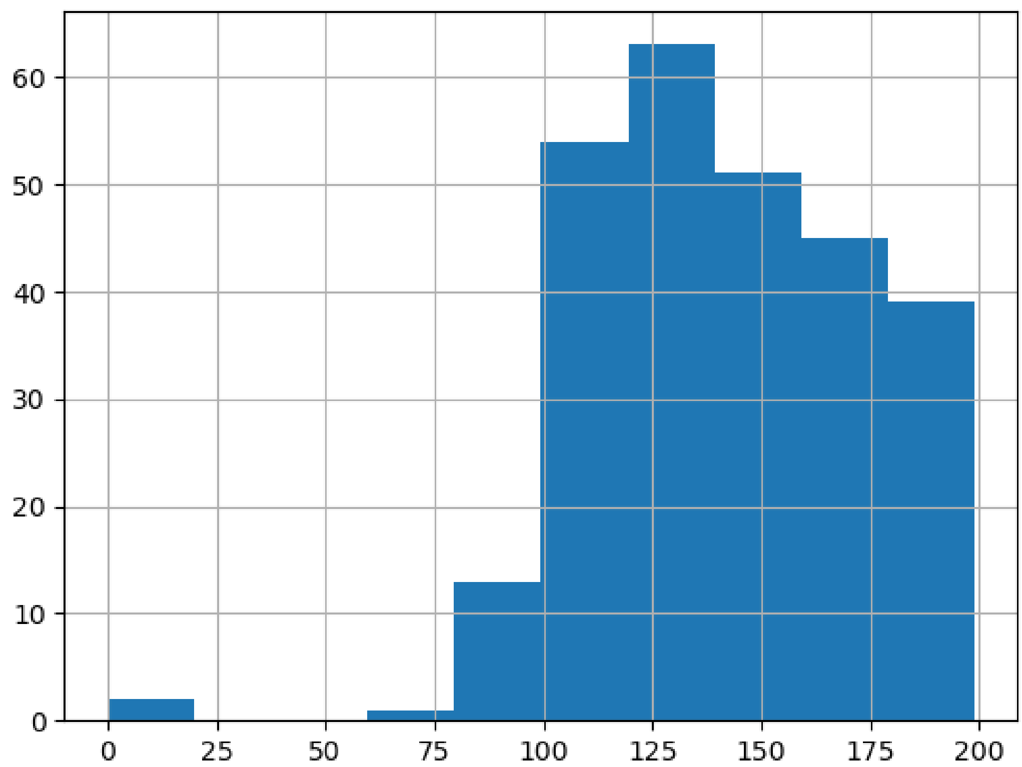
0.5 Glucose

[54]:
```
di_df['Glucose'].describe()
```

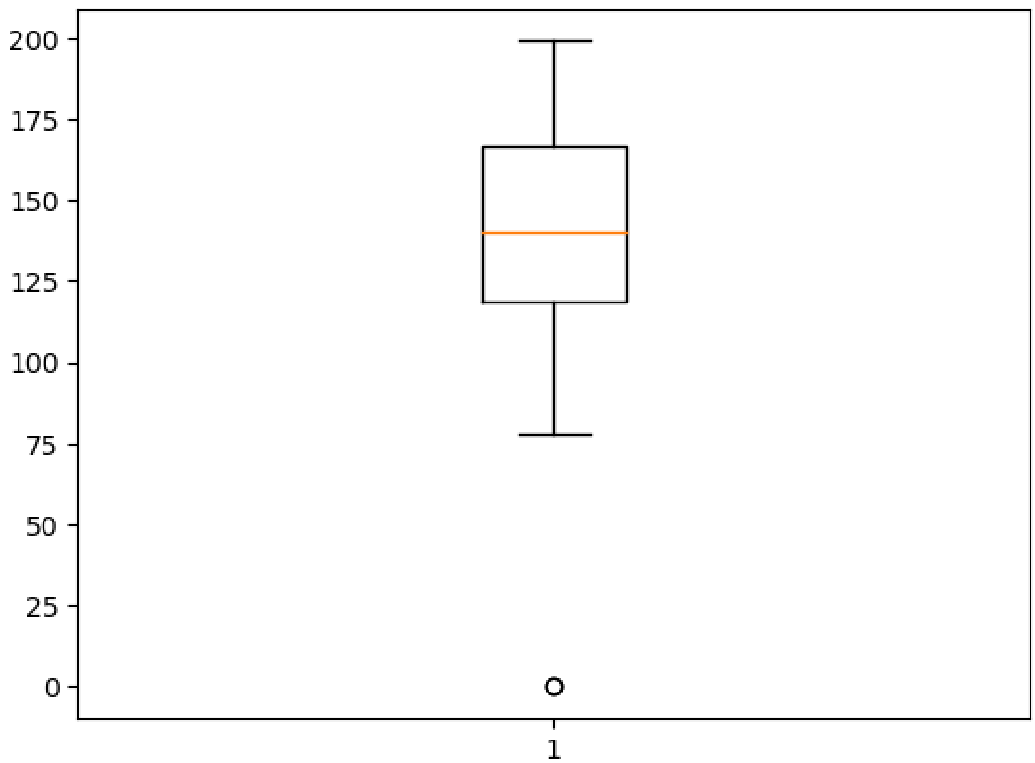
[54]:
```
count    268.000000
mean     141.257463
std       31.939622
min        0.000000
25%      119.000000
50%      140.000000
75%      167.000000
max      199.000000
Name: Glucose, dtype: float64
```

[55]:
```
di_df['Glucose'].hist()
```

[55]:
```
<AxesSubplot:>
```



[88]:
```
plt.boxplot(di_df['Glucose'])
plt.show()
```



0.5.1 insights from glucose

most diabetes ranges with glucose factor from 100 to 200 thats mean this is dangerous area

glucose is the most factor which have effect on having diabetes so this is very sensitive

we have a positive relationship between glucose and insulin thats mean we want to make a balance between them

0.6 Age

[51]:
```
di_df['Age'].describe()
```

[51]:
```
count    268.000000
mean      37.067164
std       10.968254
min       21.000000
25%       28.000000
50%       36.000000
75%       44.000000
max       70.000000
```

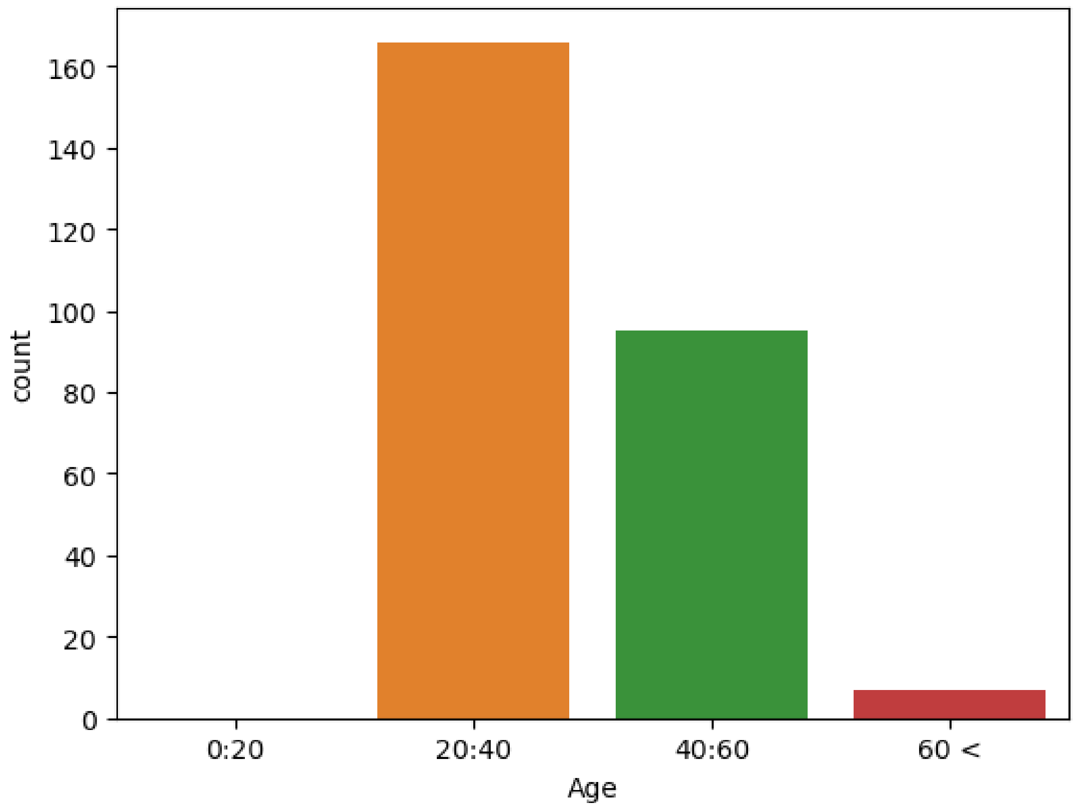
```
Name: Age, dtype: float64
```

[89]:
```
Age_value_bins = pd.cut(di_df['Age'],
                        bins = [0, 20, 40, 60, np.inf],
                        labels =['0:20', '20:40', '40:60', '60 <'])

Age_value_bins
```

[89]:
```
0       40:60
2       20:40
4       20:40
6       20:40
8       40:60
        …
755     20:40
757     40:60
759      60 <
761     40:60
766     40:60
Name: Age, Length: 268, dtype: category
Categories (4, object): ['0:20' < '20:40' < '40:60' < '60 <']
```

[90]:
```
sns.countplot(x =Age_value_bins)
```

[90]:
```
<AxesSubplot:xlabel='Age', ylabel='count'>
```



0.6.1 insights from Age

after oi split age to groups it seems somthing strange that is most of diabetes patiens are from 20 to 40 age this is very young age

but that explain the positive relationship between BMI , age and having diabetes

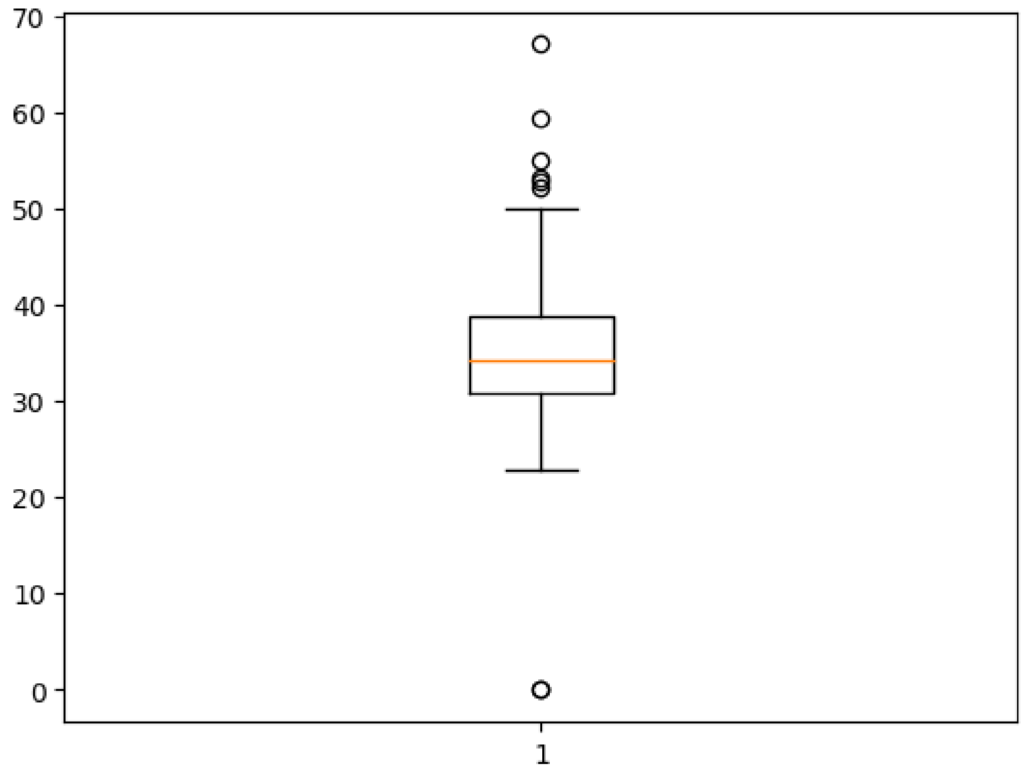
0.7 BMI

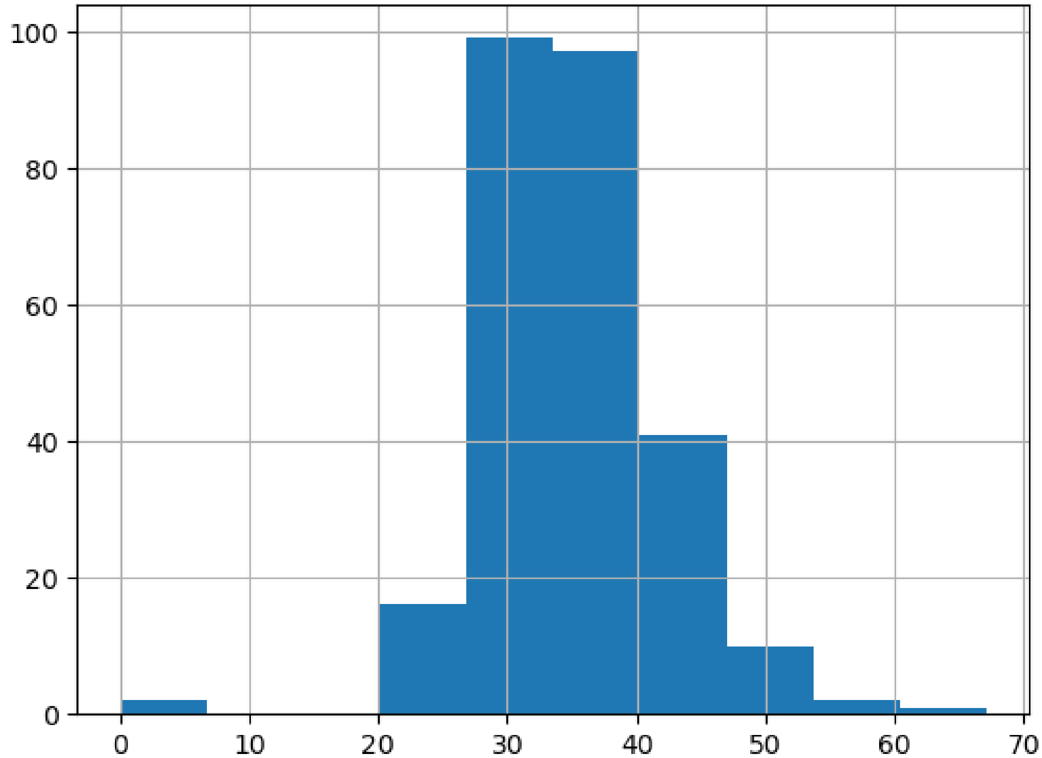
[58]:
```
di_df['BMI'].describe()
```

[58]:
```
count    268.000000
mean      35.142537
std        7.262967
min        0.000000
25%       30.800000
50%       34.250000
75%       38.775000
max       67.100000
Name: BMI, dtype: float64
```

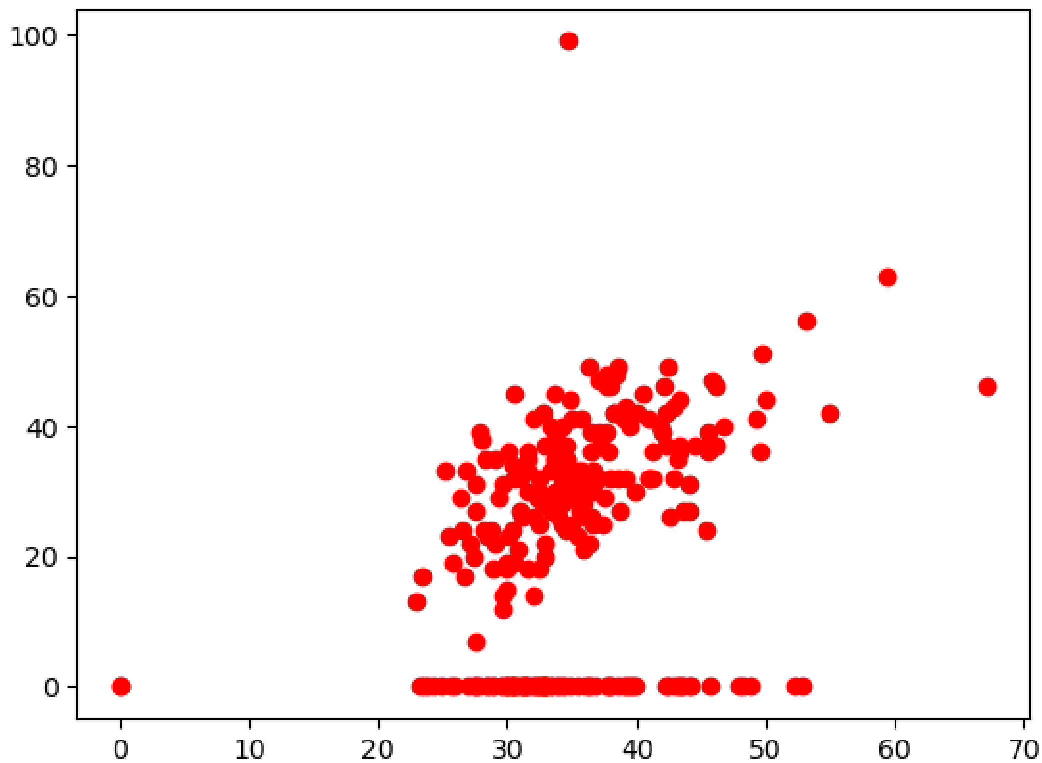
[77]:

```
plt.boxplot(di_df['BMI'])
plt.show()


di_df['BMI'].hist()
plt.show()
```





[93]:
```
plt.scatter(di_df['BMI'], di_df['SkinThickness'], color = 'r')
plt.show()
```



0.7.1 insights from BMI

from histogram i can see the dangerous area of diabetes this is from 28 to 40

as heatmap told us we have a strong positive relationship between BMI and SkinThickness so thick persons have higher metabolic rate

from previous relationship we can suppose that SkinThicknesses are most people that may have diabetes

0.8 Pregnancies

[ ]:
```
di_df['Pregnancies']
```

[64]:
```
preg_age_rel = di_df[['Age', 'Pregnancies']]
```

[65]:
```
preg_age_rel
```

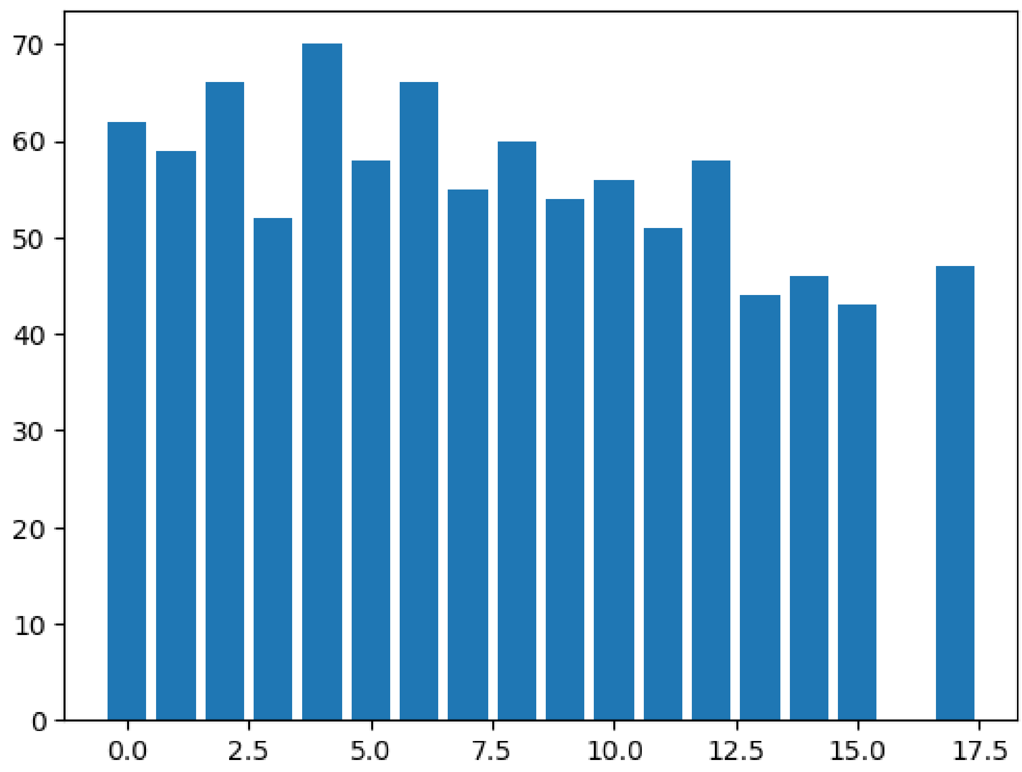
[65]:

	Age	Pregnancies
0	50	6
2	32	8
4	33	0

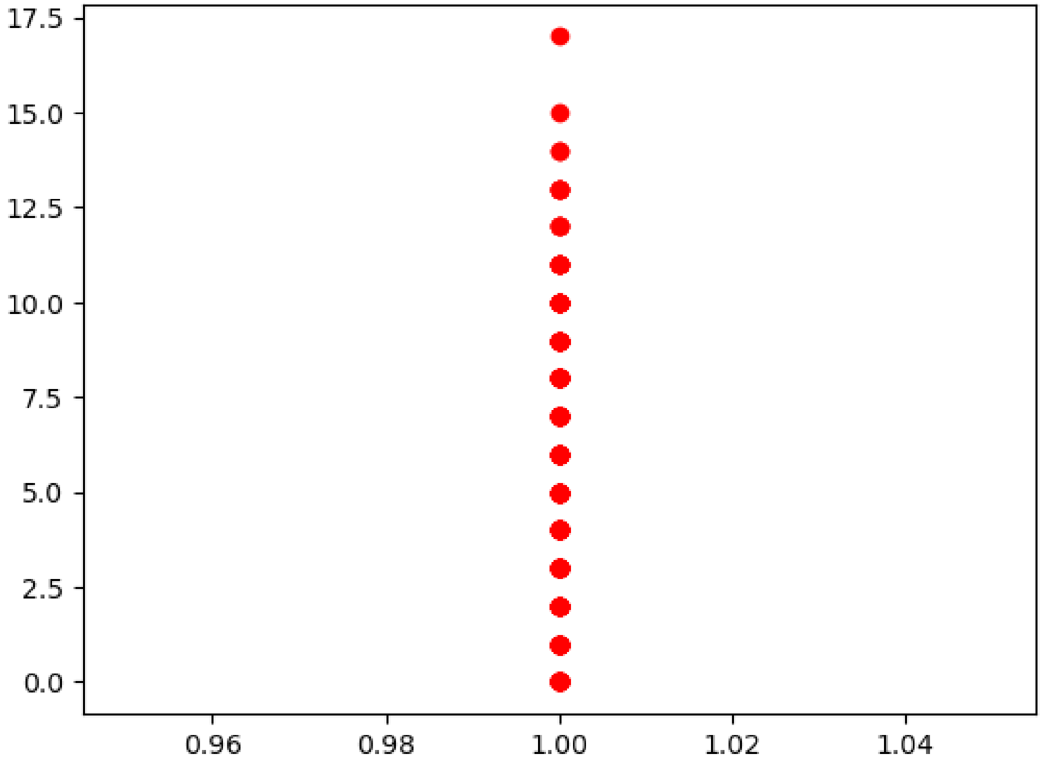
```
6      26             3
8      53             2
..    ...           ...
755    37             1
757    52             0
759    66             6
761    43             9
766    47             1

[268 rows x 2 columns]
```

[85]:
```
plt.bar(preg_age_rel['Pregnancies'], preg_age_rel['Age'])
```

[85]: <BarContainer object of 268 artists>



[71]:
```
plt.scatter(di_df['Outcome'], di_df['Pregnancies'], color = 'r')
plt.show()
```



[ ]:

```

```

0.8.1 Insights from Pregnancies

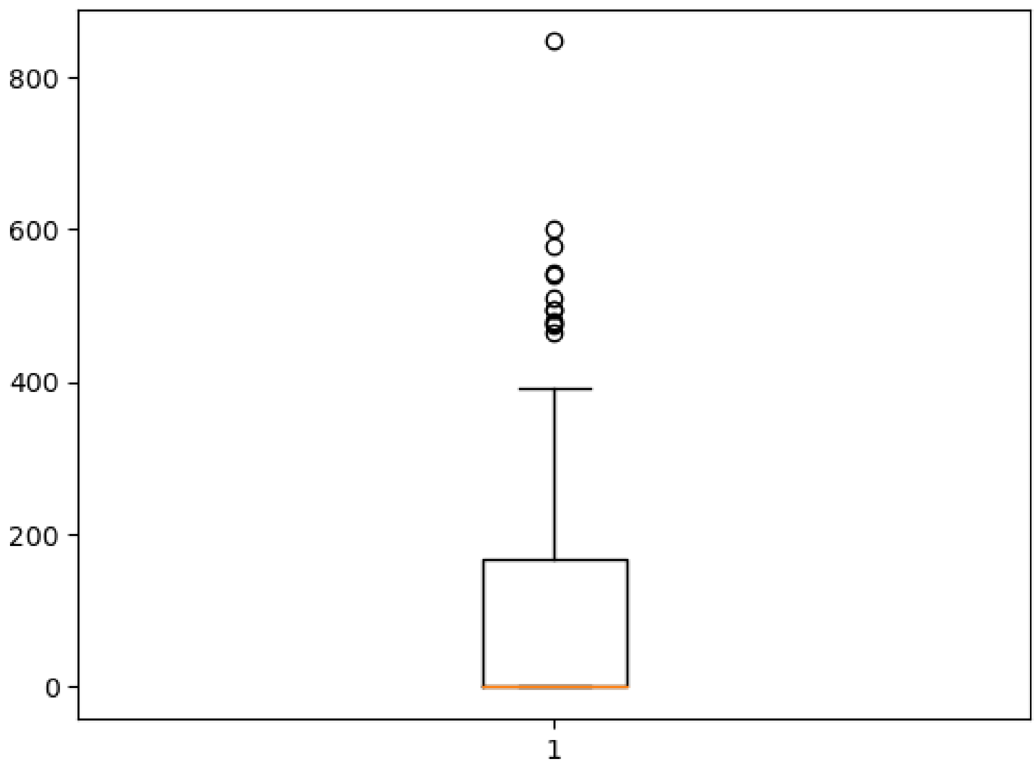
we can have a little suppose that say if num of Pregnancies increase the causation of diabetes will increase

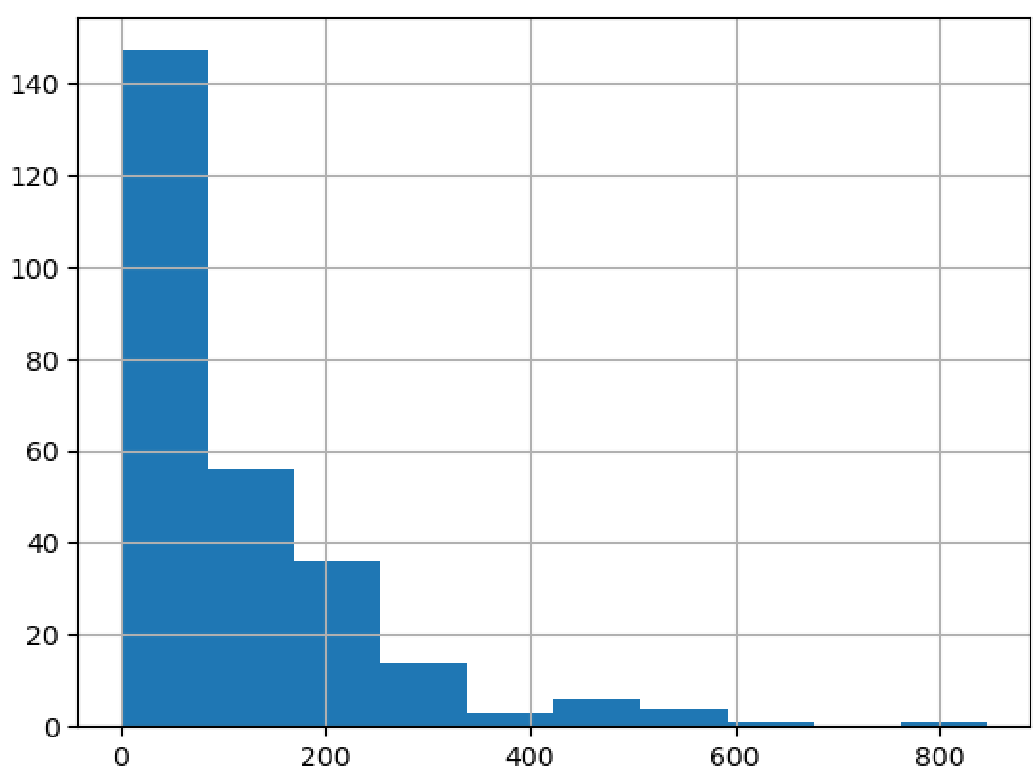
but this is not all the time but it is very dangerous because most age have diabetes from 20 to 40 and this is a prime of women

0.9 Insulin

[78]:

```
plt.boxplot(di_df['Insulin'])
plt.show()


di_df['Insulin'].hist()
plt.show()
```


800
600
400
200
0
1


140
120
100
80
60
40
20
0
0
200
400
600
800

0.9.1 insights from Insulin

we can not let our insulin to be low because it is very dangrous area from 0 to 170

Insulin have a great positive relationship with glucose and SkinThikness this is mean we want to make a balance between it and glucose

this is a positive resone to confirm my suppose that SkinThiknesses have higher possibility to have diabetes

[ ]:

```

```