Diabetics Data Analysis

Project Purpose

This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases. The objective of the dataset is to diagnostically predict whether a patient has diabetes based on certain diagnostic measurements included in the dataset. Several constraints were placed on the selection of these instances from a larger database. In particular, all patients here are females at least 21 years old of Pima Indian heritage.2

MetaData

Pregnancies: Number of times pregnant

Glucose: The plasma glucose concentration in the oral glucose tolerance test after two hours

BloodPressure: Diastolic blood pressure (mm Hg)

SkinThickness: Triceps skin fold thickness (mm)

Insulin: 2-Hour serum insulin (mu U/ml)

BMI: Body mass index (weight in kg/(height in m)^2)

DiabetesPedigreeFunction: This function calculates the likelihood of having diabetes based on the lineage of a descendant

Age: Age (years)

Outcome: Class variable (have the disease (1) or not (0))

Import required Libraries

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

# to suppress warnings
import warnings
warnings.filterwarnings('ignore')
```

Read dataset

In [2]:
```
df= pd.read_csv("C:/Users/39375/Desktop/Gayu/VIRTUAL INTERNSHIP/MeriSkill/diabetics.csv"
```

In [3]:
```
df
```

Out[3]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Ou
0	6	148	72	35	0	33.6	0.627	50	
1	1	85	66	29	0	26.6	0.351	31	
2	8	183	64	0	0	23.3	0.672	32	
3	1	89	66	23	94	28.1	0.167	21	
4	0	137	40	35	168	43.1	2.288	33	
...	...	...	...	...	...	...	...	...	
763	10	101	76	48	180	32.9	0.171	63	
764	2	122	70	27	0	36.8	0.340	27	
765	5	121	72	23	112	26.2	0.245	30	
766	1	126	60	0	0	30.1	0.349	47	
767	1	93	70	31	0	30.4	0.315	23	

768 rows × 9 columns

Exploratory Data Analysis

Show first N rows of Dataframe

In [4]:
```
df.head(10)
```

Out[4]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outc
0	6	148	72	35	0	33.6	0.627	50	
1	1	85	66	29	0	26.6	0.351	31	
2	8	183	64	0	0	23.3	0.672	32	
3	1	89	66	23	94	28.1	0.167	21	
4	0	137	40	35	168	43.1	2.288	33	
5	5	116	74	0	0	25.6	0.201	30	
6	3	78	50	32	88	31.0	0.248	26	
7	10	115	0	0	0	35.3	0.134	29	
8	2	197	70	45	543	30.5	0.158	53	
9	8	125	96	0	0	0.0	0.232	54	

Check shape of the dataset

In [5]:
```
df.shape
```

Out[5]:
```
(768, 9)
```

we have 768 rows and 9 columns

Variable name in Dataset

In [6]:
```
df.columns
```

Out[6]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

Information about the Dataset

In [7]:
```
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
```

Describe the Dataset

In [8]:
```
df.describe()
```

Out[8]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFun
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.00
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.47
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.33
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.07
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.24
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.37
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.62
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.42

Number of Unique values in variables

In [9]:
```
df.nunique()
```

Out[9]:
```
Pregnancies                 17
Glucose                    136
BloodPressure               47
SkinThickness               51
Insulin                    186
BMI                        248
DiabetesPedigreeFunction   517
Age                         52
Outcome                      2
dtype: int64
```

The Distribution of the Outcome variable

In [10]:
```
df["Outcome"].value_counts()*100/len(df)
```

Out[10]:
```
0    65.104167
1    34.895833
Name: Outcome, dtype: float64
```

Data Preprocessing

Check duplicate values in Dataset

In [11]:
```
df.duplicated().sum()
```

Out[11]:
```
0
```

There are no duplicate values in the dataset.

check Null values in dataset

In [12]:
```
df.isna().sum()
```

Out[12]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

There are no null values in the dataset.

Check 0 values in Dataset

In [13]:
```
(df[df.columns] == 0).sum()
```

Out[13]:
```
Pregnancies                 111
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
Age                           0
Outcome                     500
dtype: int64
```

Replace 0 values with Median

In [14]:
```
for i in ["Glucose","BMI","Insulin","BloodPressure"]:
    df[i].replace({0:df[i].median()},inplace = True)
```

Again checking for 0 values

In [15]:
```
(df[df.columns] == 0).sum()
```

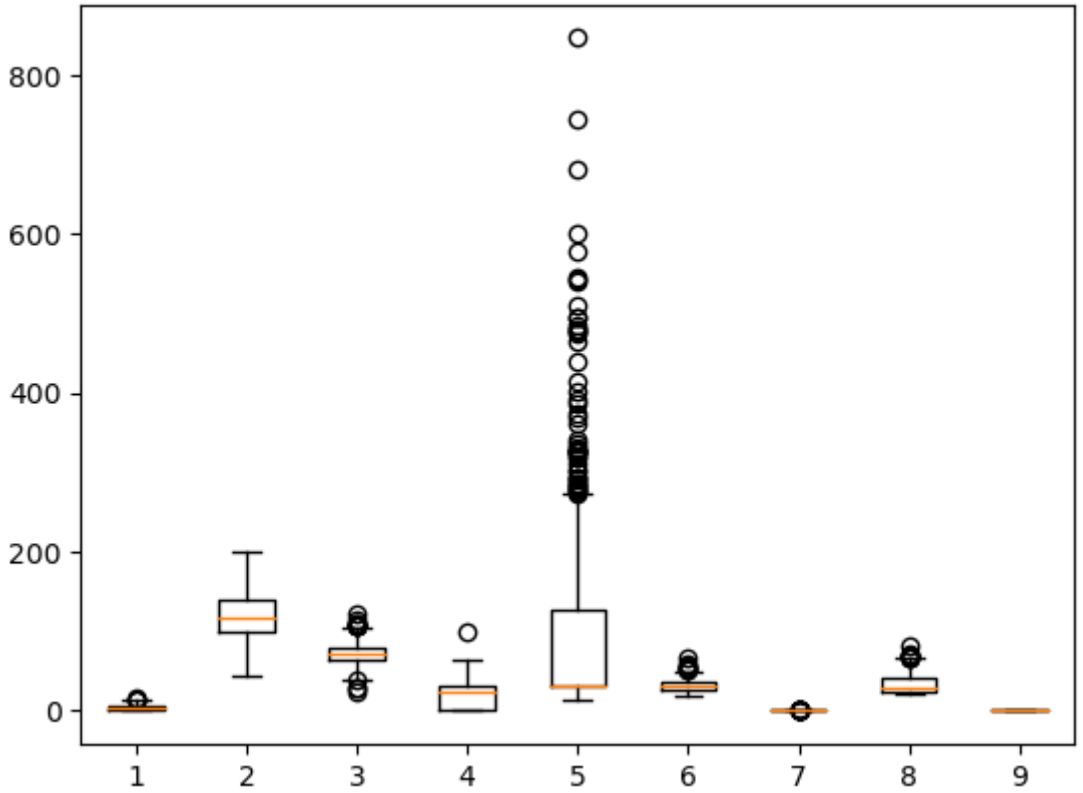
Out[15]:
```
Pregnancies                 111
Glucose                       0
BloodPressure                 0
SkinThickness               227
Insulin                       0
BMI                           0
DiabetesPedigreeFunction      0
Age                           0
Outcome                     500
dtype: int64
```

Now the zero values are replaced by median value.

Outlier Observation Analysis

Check outliers in variables

In [16]:
```
plt.boxplot(df);
```



There are lot of outliers.

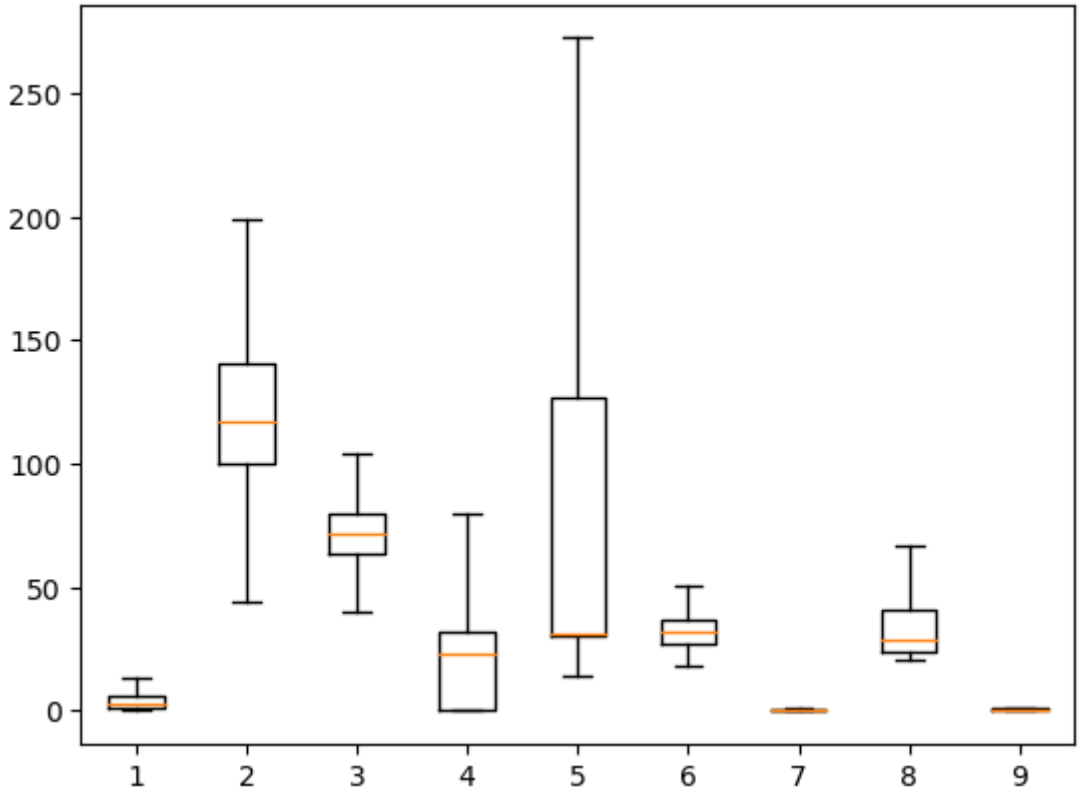
Outlier Detection

In [17]:
```
def outlier_removal():
    l = ["BMI","Glucose","SkinThickness","Age","BloodPressure","Insulin","Pregnancies","
    for i in l:
        x = np.quantile(df[i],[0.25,0.75])
        iqr = x[1]-x[0]
        uw = x[1]+1.5*iqr
        lw = x[0]-1.5*iqr
        df[i]  = np.where(df[i]>uw,uw,(np.where(df[i]<lw,lw,df[i])))

outlier_removal()
```

Outlier recheck

In [18]:
```
plt.boxplot(df);
```

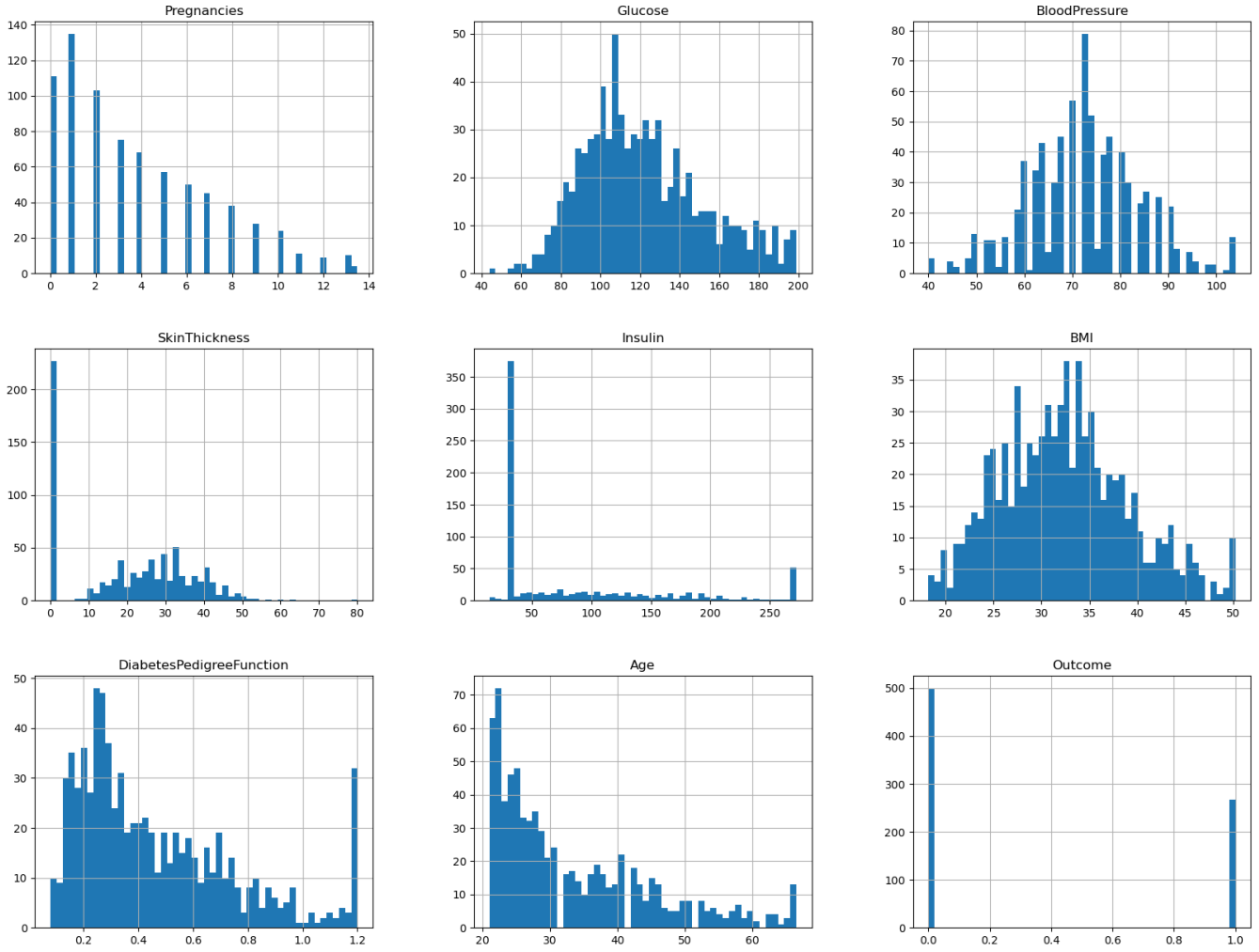


After the outlier detection and removal , all outliers are processed.

Visualization of the dataset

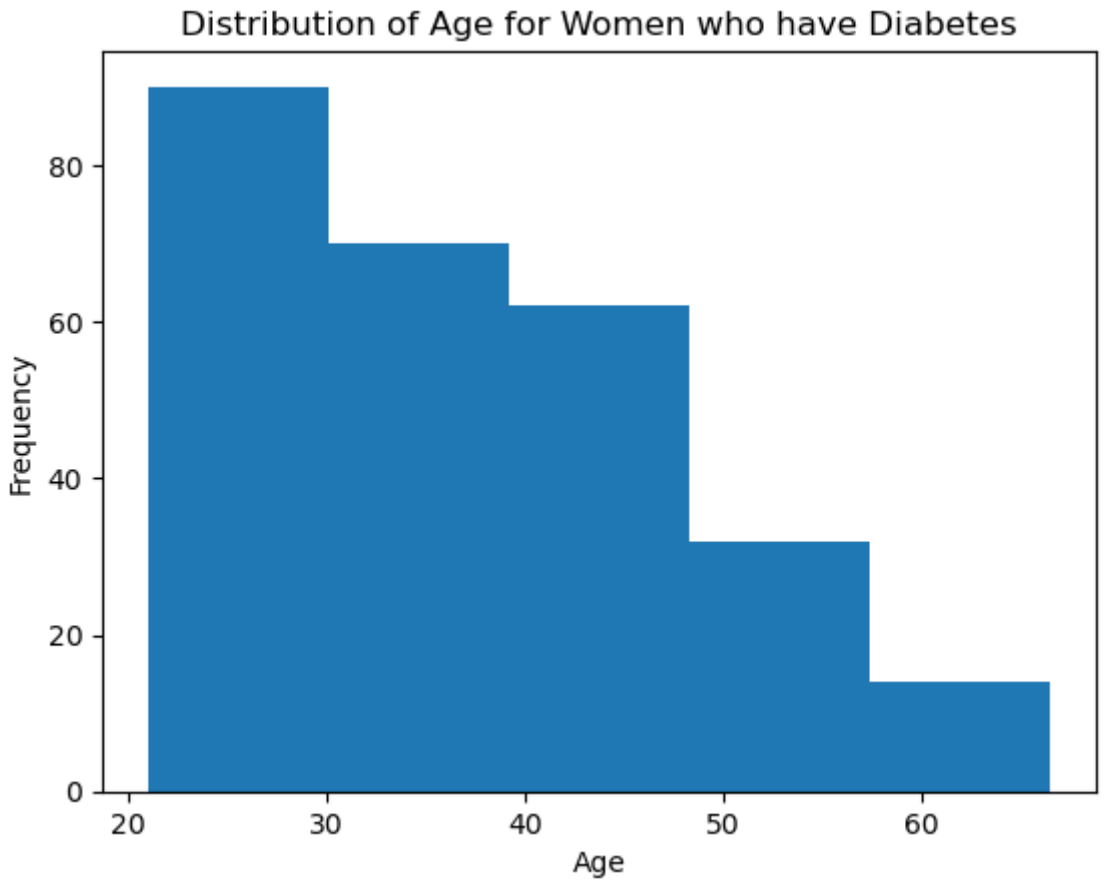
Data distribution of variables

In [19]:
```
df.hist(bins=50, figsize=(20,15));
```



The number of women in different age group with Diabetics

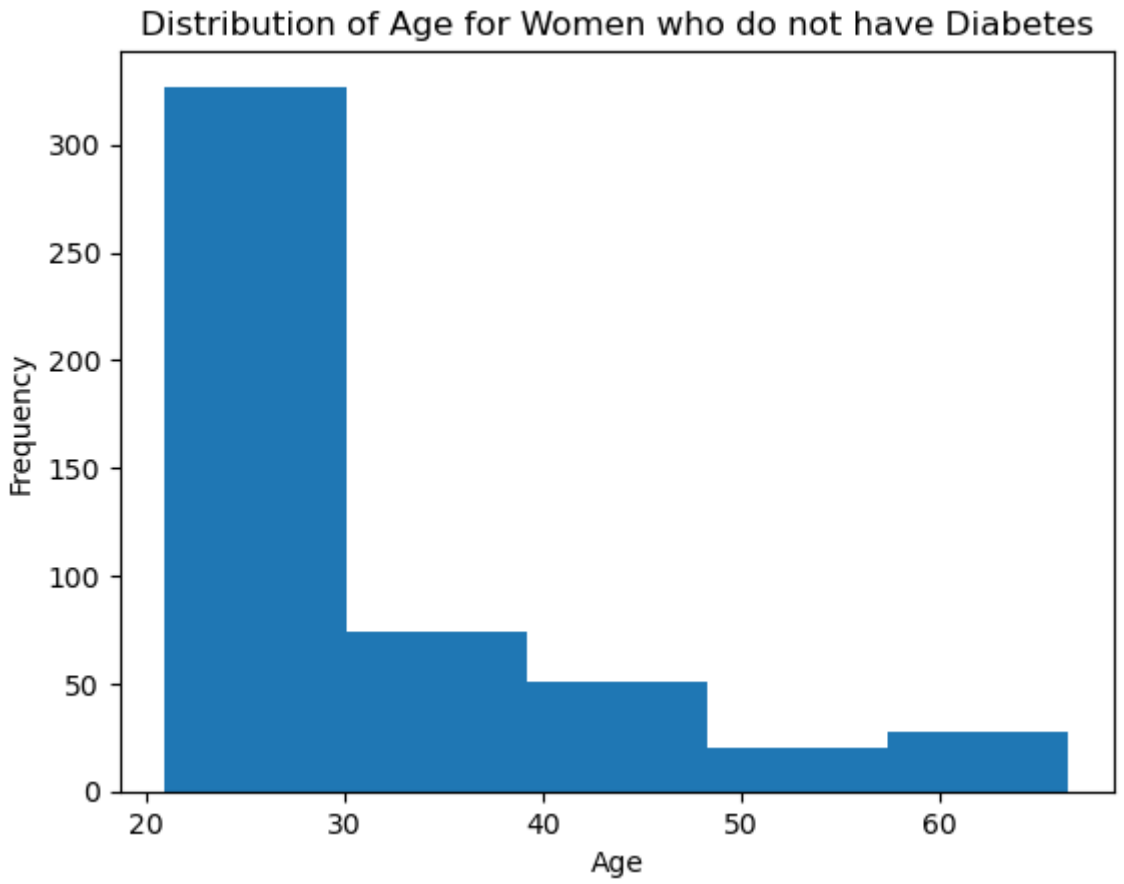
In [20]:
```
plt.hist(df[df['Outcome']==1]['Age'],bins=5)
plt.title('Distribution of Age for Women who have Diabetes')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



The age range of 22 to 30 has the highest proportion of women with diabetes. As age increases, the frequency of women with diabetes decreases.

The number of women in different age group with No Diabetics

In [21]:
```
plt.hist(df[df['Outcome']==0]['Age'],bins=5)
plt.title('Distribution of Age for Women who do not have Diabetes')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



Women without diabetes are predominantly in the 22 to 35 age bracket. This age bracket also has the highest diabetes risk among women.

Checking correlation between variables

In [22]:
```
df.corr()
```

Out[22]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabet
Pregnancies	1.000000	0.126856	0.210906	-0.084349	-0.061192	0.027145	
Glucose	0.126856	1.000000	0.220199	0.071090	0.338429	0.233953	
BloodPressure	0.210906	0.220199	1.000000	0.013501	-0.033847	0.286410	
SkinThickness	-0.084349	0.071090	0.013501	1.000000	0.464759	0.382740	
Insulin	-0.061192	0.338429	-0.033847	0.464759	1.000000	0.207474	
BMI	0.027145	0.233953	0.286410	0.382740	0.207474	1.000000	
DiabetesPedigreeFunction	-0.017398	0.118457	0.012305	0.177920	0.191870	0.138541	
Age	0.549695	0.268912	0.332898	-0.119170	-0.040448	0.035861	
Outcome	0.220392	0.492782	0.168971	0.073125	0.147295	0.313030	

Correlation of Output variable with other variables in decreasing order

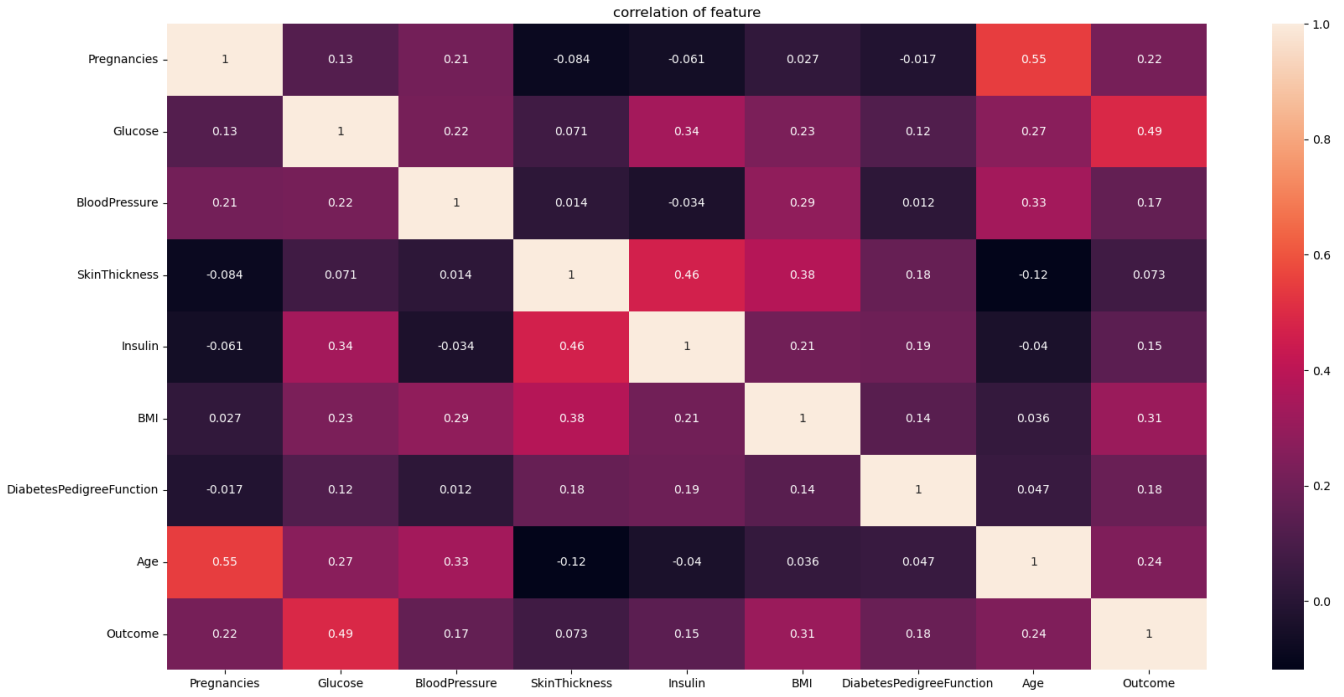
In [23]:
```
df.corr()['Outcome'].sort_values(ascending=False)
```

Out[23]:
```
Outcome                     1.000000
Glucose                     0.492782
BMI                         0.313030
Age                         0.242702
Pregnancies                 0.220392
DiabetesPedigreeFunction    0.184969
BloodPressure               0.168971
Insulin                     0.147295
SkinThickness               0.073125
Name: Outcome, dtype: float64
```

Heatmap of Correlation

In [24]:
```
plt.figure(figsize = (20,10))
sns.heatmap(df.corr(), annot=True)
plt.title("correlation of feature")
```

Out[24]:
```
Text(0.5, 1.0, 'correlation of feature')
```

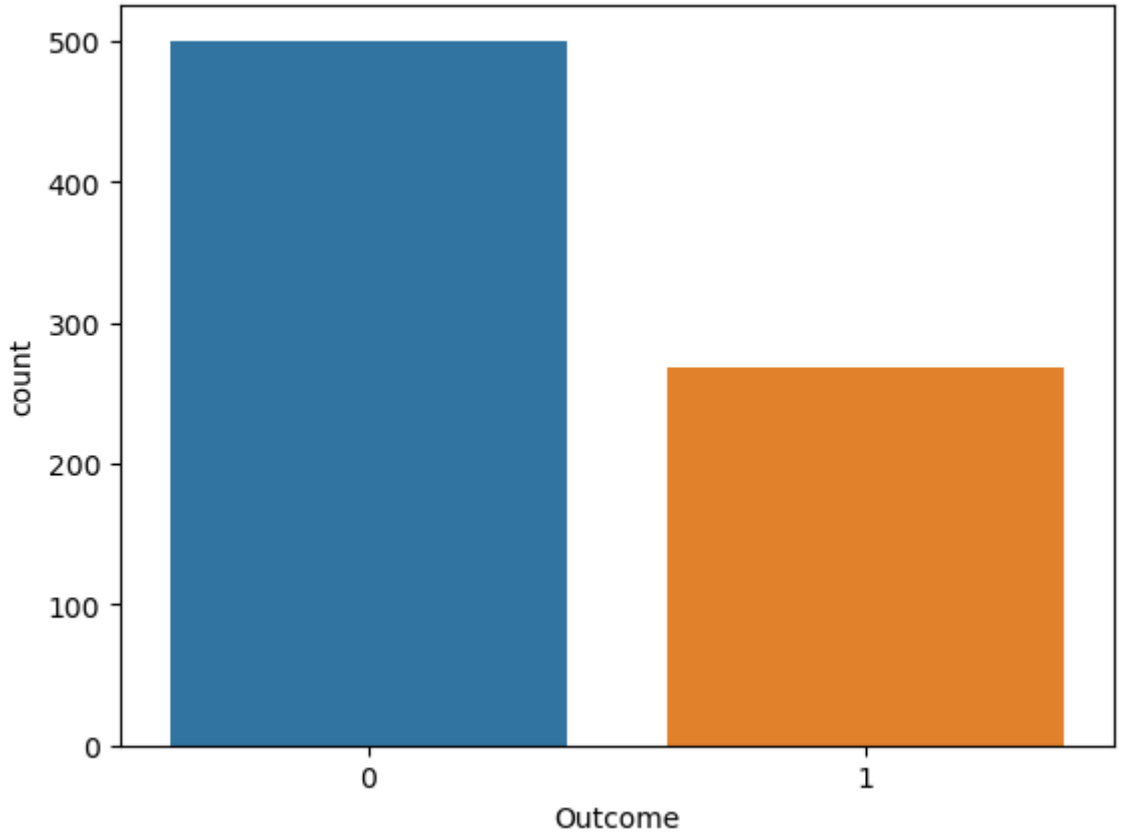


According to the correlation outcome ratios, the most important features are BMI, age, and pregnancies (external factors), and glucose and insulin (internal factors), in that order. The least important features are skin thickness and blood pressure. The main conclusions are:

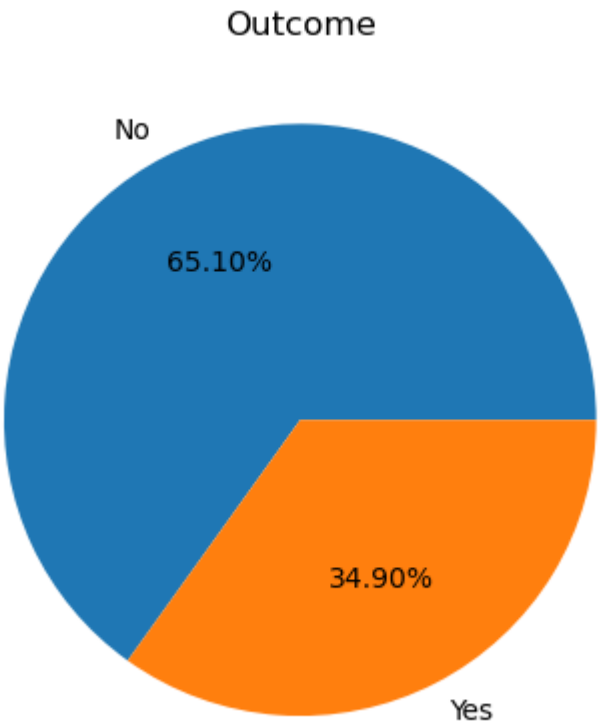
1. Maintain a healthy BMI to prevent high glucose and insulin levels.
2. Monitor your glucose and insulin levels as you age.
3. If you are pregnant, be careful about your glucose and insulin levels.

Output variable distribution

In [25]:
```
sns.countplot(x ='Outcome', data = df);
```



In [26]:
```
plt.title('Outcome')
plt.pie(df['Outcome'].value_counts(),labels=['No','Yes'], autopct='%1.2f%%')
plt.show()
```

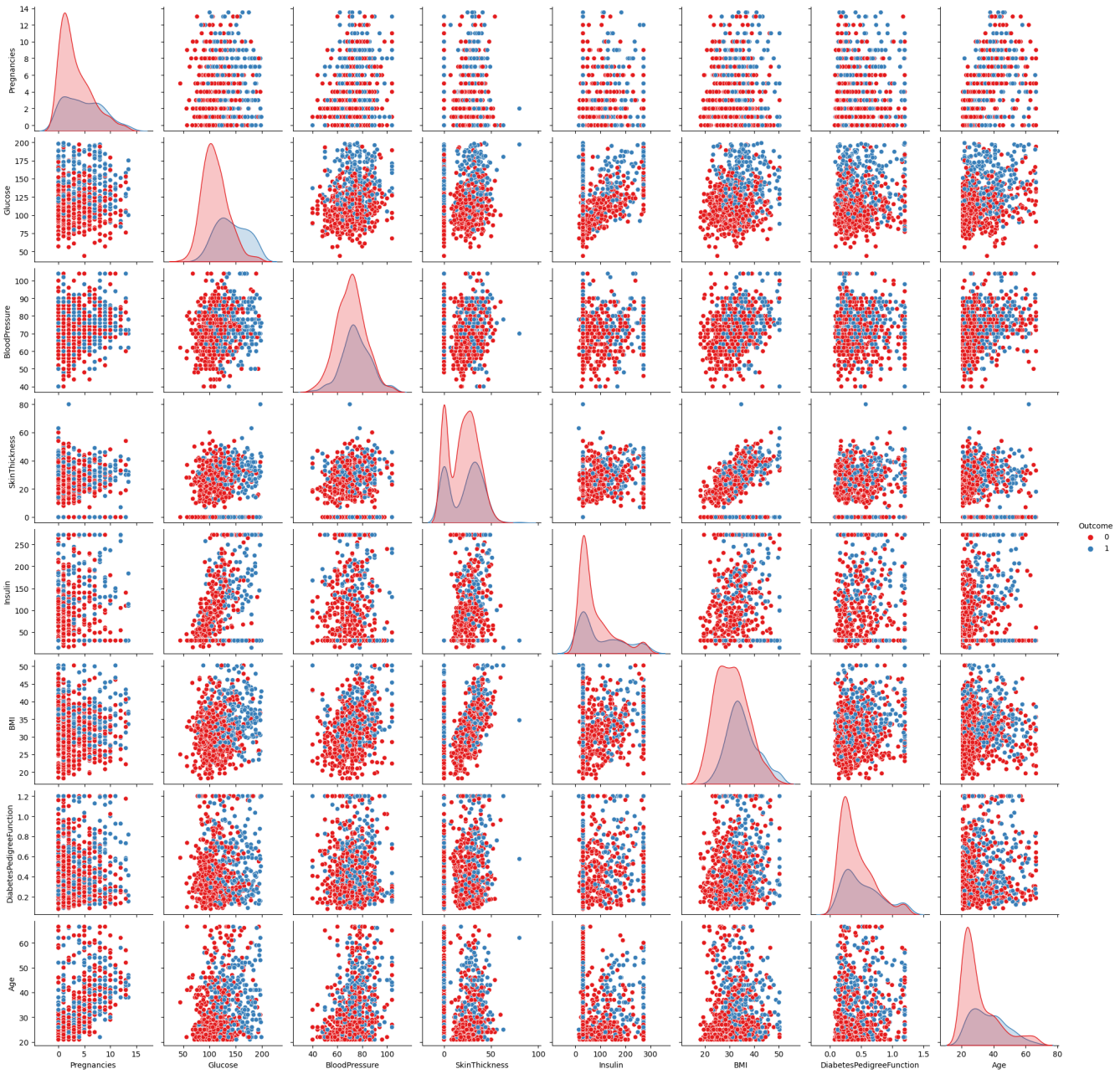


The percentage of Diabetics in Pregancies are 34.90% and non- diabetics are 65.10%

Pairplot of dataset variables relation with Outcome

In [27]:
```
sns.pairplot(df, hue='Outcome', palette="Set1")
```

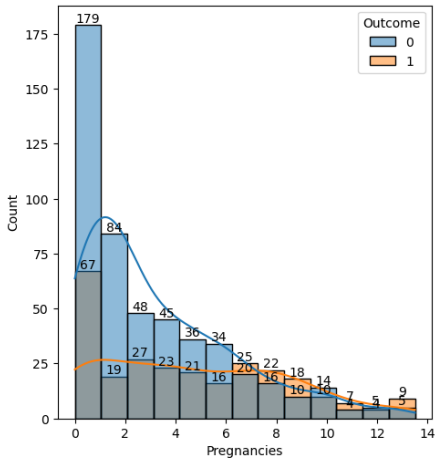
Out[27]:
```
<seaborn.axisgrid.PairGrid at 0x26304844df0>
```

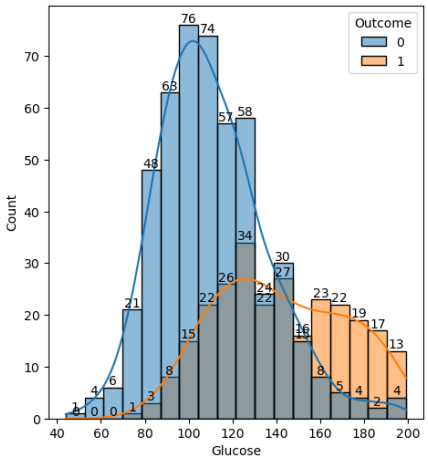


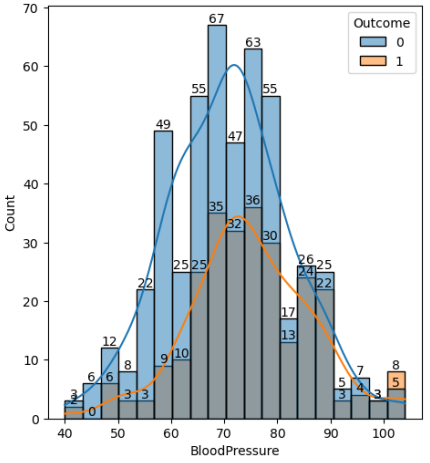
High glucose levels in pregnancy make diabetes more likely. A combination of high glucose levels and a BMI above 30 boosts the risk of diabetes.The risk of diabetes increases with high glucose levels and other variables.

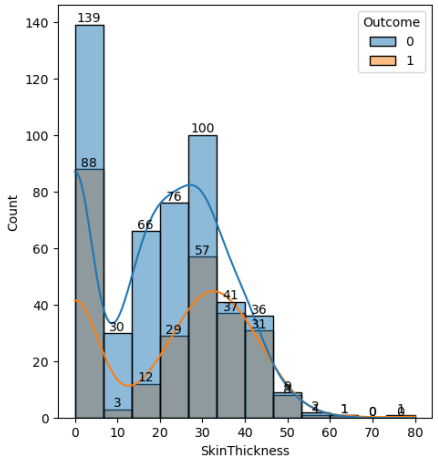
Histplot of dataset variables with Outcome

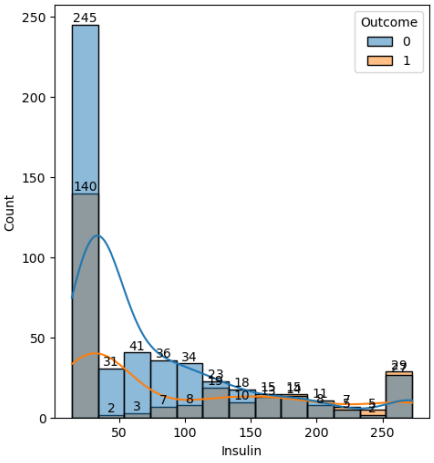
In [28]:
```
pno = 1
plt.figure(figsize=(18,20))
for i in df.columns:
        if pno<9:
            plt.subplot(3,3,pno)
            ax = sns.histplot(data = df , x = i , hue = df.Outcome , kde = True);
            plt.xlabel(i)
            pno+=1
            for i in ax.containers:      #to set a label on top of the bars.
                ax.bar_label(i,)
```

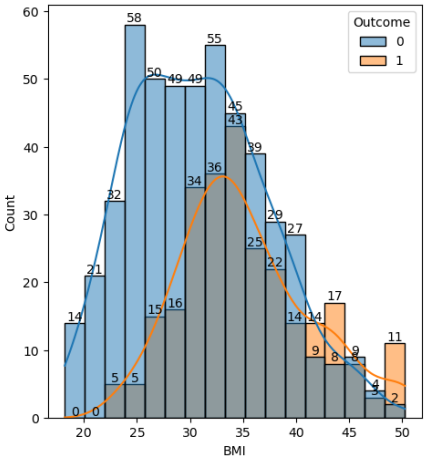


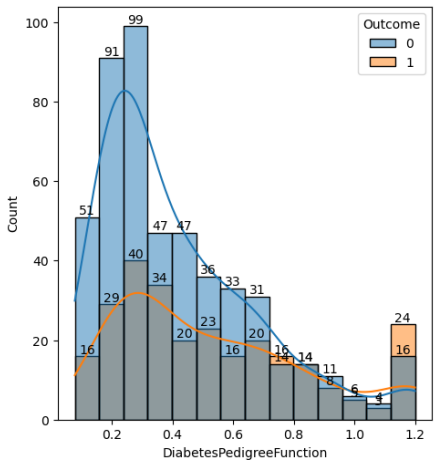


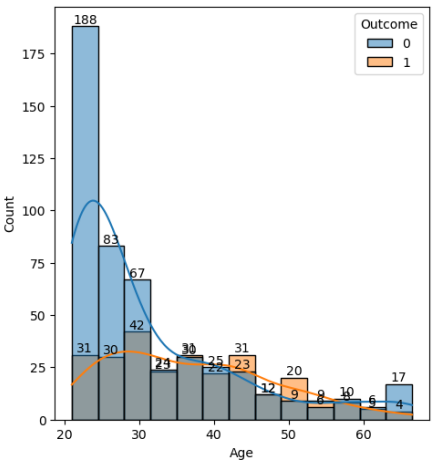












Key Insights

The following factors affect the risk of diabetes, according to the data analysis:

1. Pregnancies: More pregnancies mean higher diabetes risk.
2. Glucose: Diabetes is more likely with high glucose levels (above 140).
3. Blood pressure: Blood pressure between 60 and 90 has more diabetic people than other ranges.

4. Skin thickness: Skin thickness makes diabetes more likely.
5. Insulin: Insulin levels influence diabetes, and higher insulin levels increase the diabetes risk.
6. BMI: Higher BMI (above 30) increases the risk of diabetes.
7. Age: Age makes diabetes more likely.