Predict whether or not a patient has diabetes with Logistic regression

In [1]:
```
#importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

Reading data

In [2]:
```
df = pd.read_csv('data/diabetes.csv')
df.head()
```

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

In [3]:
```
df.shape
```

Out[3]:
```
(768, 9)
```

In [4]:
```
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
```

Exploratory Data Analysis

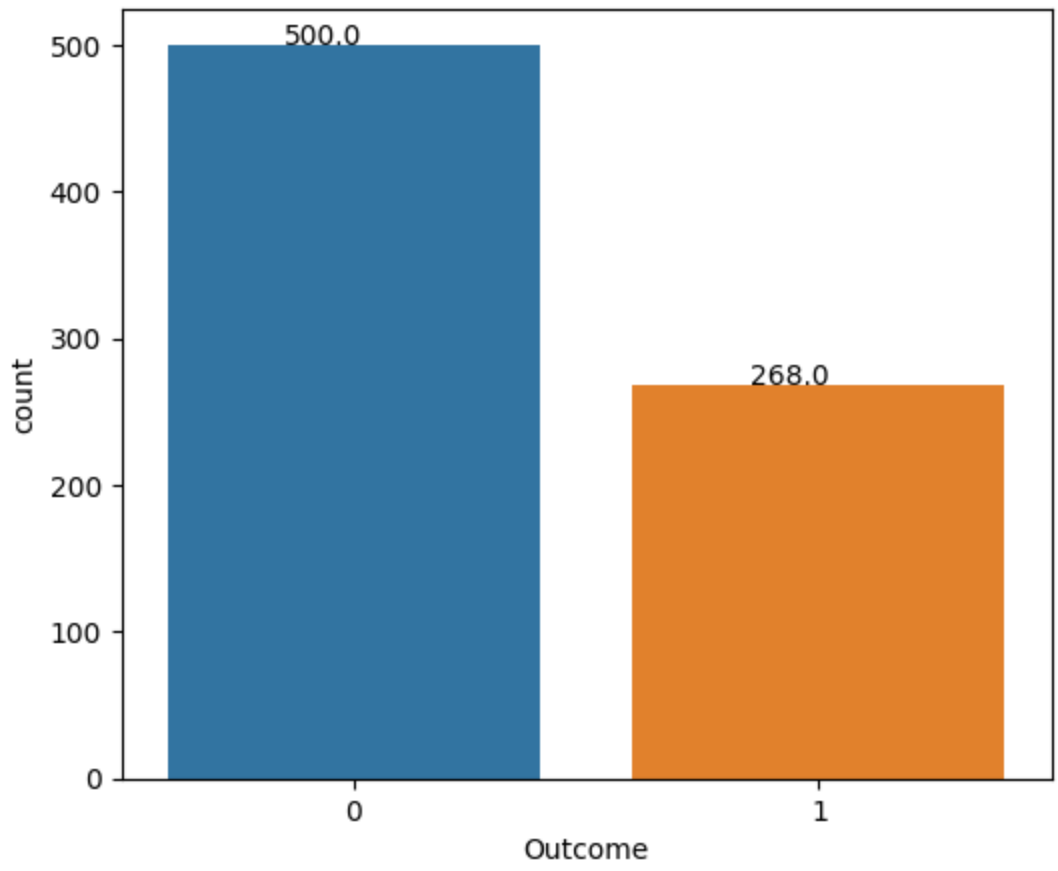
In [5]:
```
df.describe().T
```

Out[5]:

	count	mean	std	min	25%	50%	75%	max
Pregnancies	768.0	3.845052	3.369578	0.000	1.00000	3.0000	6.00000	17.00
Glucose	768.0	120.894531	31.972618	0.000	99.00000	117.0000	140.25000	199.00
BloodPressure	768.0	69.105469	19.355807	0.000	62.00000	72.0000	80.00000	122.00
SkinThickness	768.0	20.536458	15.952218	0.000	0.00000	23.0000	32.00000	99.00
Insulin	768.0	79.799479	115.244002	0.000	0.00000	30.5000	127.25000	846.00
BMI	768.0	31.992578	7.884160	0.000	27.30000	32.0000	36.60000	67.10
DiabetesPedigreeFunction	768.0	0.471876	0.331329	0.078	0.24375	0.3725	0.62625	2.42
Age	768.0	33.240885	11.760232	21.000	24.00000	29.0000	41.00000	81.00
Outcome	768.0	0.348958	0.476951	0.000	0.00000	0.0000	1.00000	1.00

- The columns Glucoes, BloodPressure, SkinThickness, Insulin and BMI have min value = 0 which is not possible.
- Pregnancies column has outliers

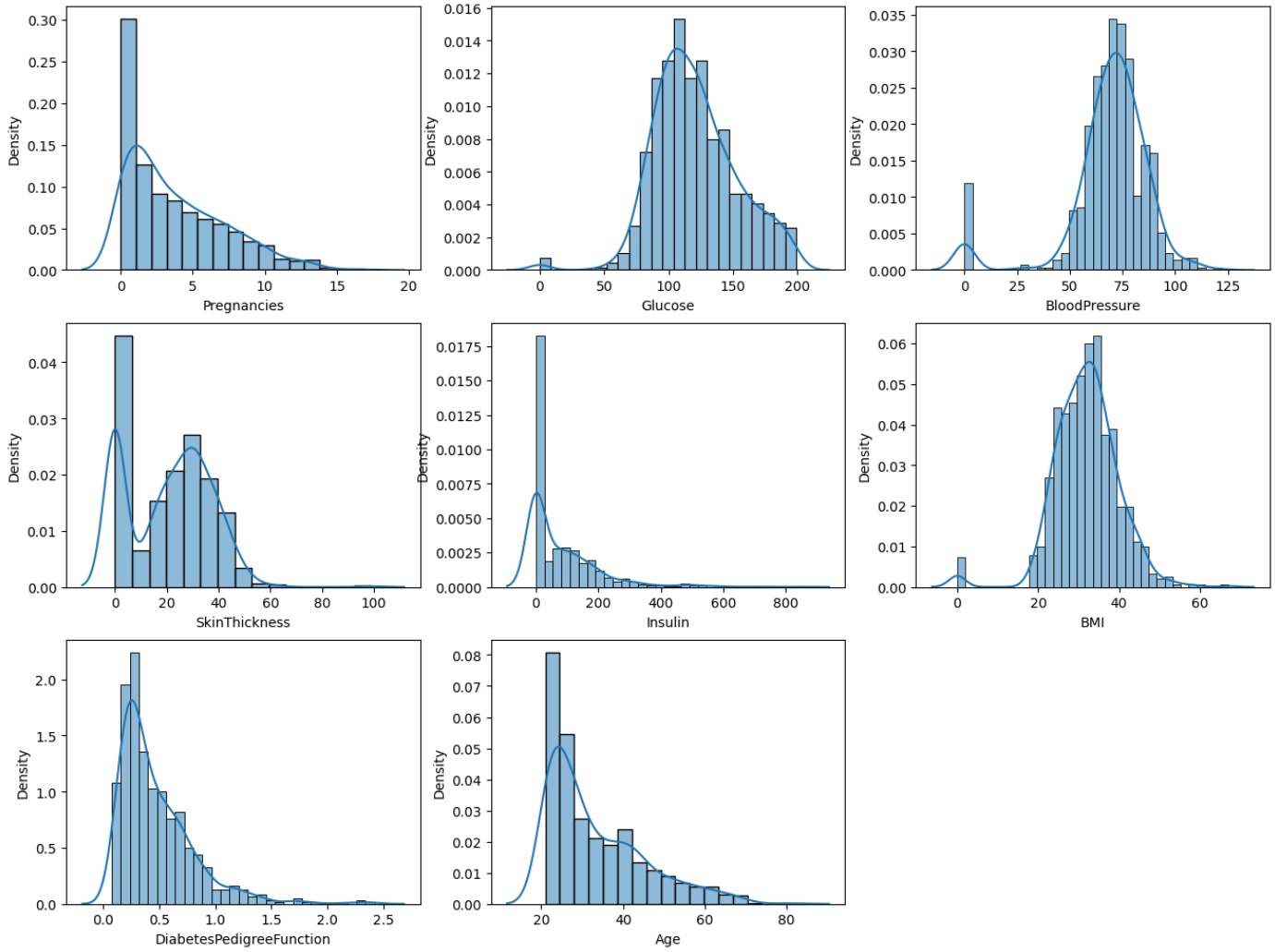
In [6]:
```
#visualizing target
plt.figure(figsize=(6,5))

ax = sns.countplot(x=df['Outcome'], data=df)
for p in ax.patches:
   ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.25, p.get_height()+0.01))

plt.show()
```



- Imabalanced dataset

- 500 entries donot have diabets while only 268 datapoints are diabetic

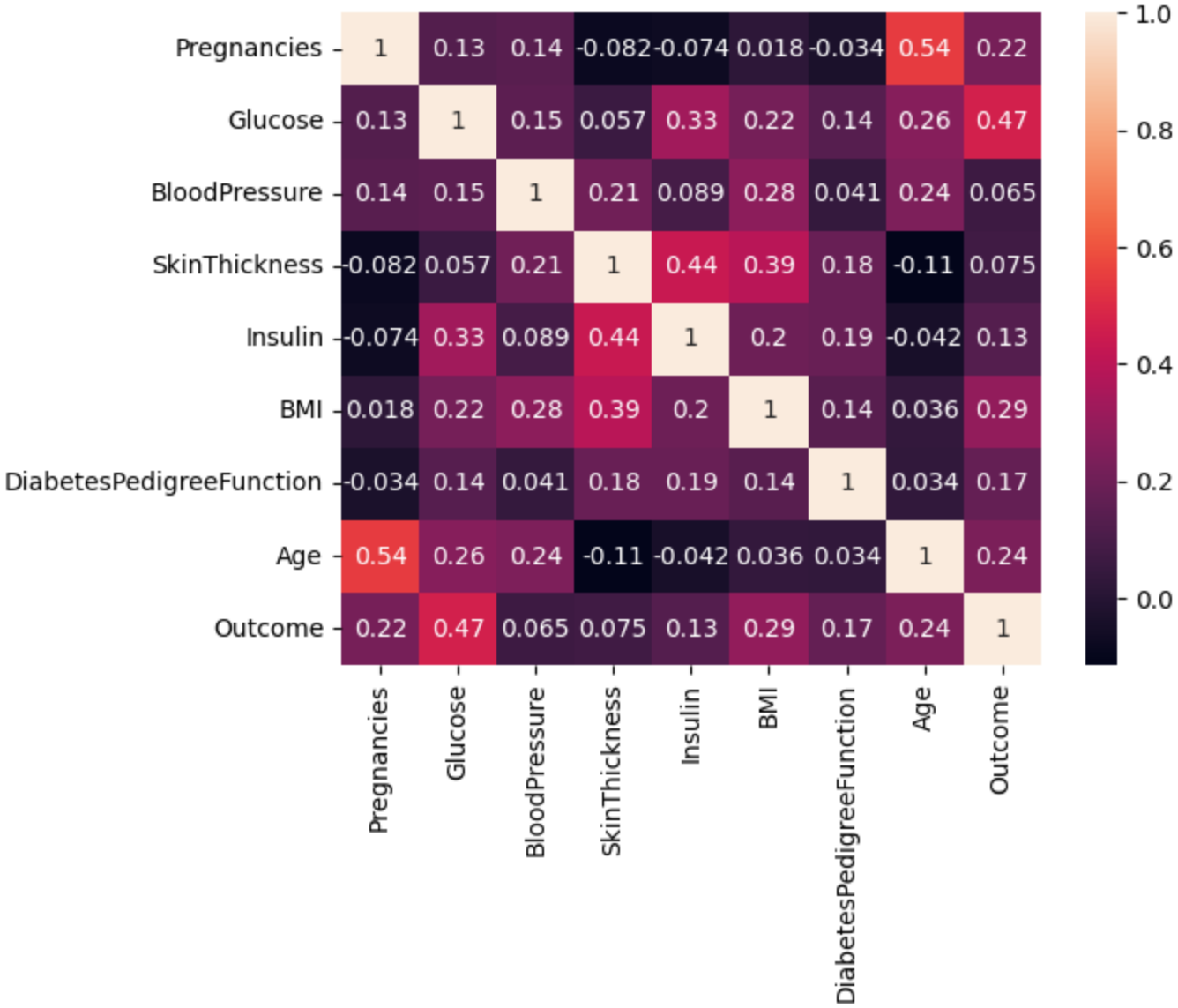
In [7]:
```
#distributions of features

features = df.columns[:-1]

plt.figure(figsize=(16,12))

for i, col in enumerate(features, 1):
    plt.subplot(3,3,i)
    sns.histplot(data=df, x=col, kde=True, stat='density', kde_kws=dict(cut=3))
```



- Neglecting the improper min value = 0 Glucose, BMI and BloodPressure follows normal distribution
- All other features follow right skewed distribution

In [9]:
```
sns.heatmap(df.corr(), annot=True)
```

Out[9]:
```
<AxesSubplot: >
```



- There are no multicollinearity between features

Data preprocessing

In [10]:
```
#checking for null values

df.isnull().sum()
```

Out[10]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [12]:
```
#checking for duplicates
df.duplicated().sum()
```

Out[12]:
```
0
```

In [13]:
```
#handling min values = 0 entries
```

```
df[['Glucose','BloodPressure','SkinThickness','Insulin','BMI']] = df[['Glucose','BloodPr
```

In [16]:
```
df.isnull().sum()
```

Out[16]:
```
Pregnancies                 0
Glucose                     5
BloodPressure              35
SkinThickness             227
Insulin                   374
BMI                        11
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [17]:
```
#Replacin the null values with the mean of that column:

df['Glucose'].fillna(df['Glucose'].mean(), inplace =True)

df['BloodPressure'].fillna(df['BloodPressure'].mean(), inplace =True)

df['SkinThickness'].fillna(df['SkinThickness'].mean(), inplace =True)

df['Insulin'].fillna(df['Insulin'].mean(), inplace =True)

df['BMI'].fillna(df['BMI'].mean(), inplace =True)
```

In [18]:
```
df.isnull().sum()
```

Out[18]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [29]:
```
#seprating features and target

X = df.drop('Outcome', axis=1)
y = df['Outcome']
```

In [30]:
```
#splitting dataset into train and test set

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
```

Applying SMOTE for handling imbalnced dataset

In [31]:
```
print("Percentage of Positive Values in training data before Smote :",y_train.value_coun
print("Percentage of Negative Values in training data before Smote :",y_train.value_coun
```

```
Percentage of Positive Values in training data before Smote : 34.69055374592834 %
Percentage of Negative Values in training data before Smote : 65.30944625407166 %
```

In [32]:
```
#appliying SMOTE
from imblearn.over_sampling import SMOTE
smote = SMOTE()
X_train,y_train = smote.fit_resample(X_train,y_train)
```

In [33]:
```
print("Percentage of Positive Values in training data after Smote :",y_train.value_count
```

```
print("Percentage of Negative Values in training data after Smote :",y_train.value_count
```

```
Percentage of Positive Values in training data after Smote : 50.0 %
Percentage of Negative Values in training data after Smote : 50.0 %
```

In [34]:
```
#scaling the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Model building

In [35]:
```
lr = LogisticRegression()
lr.fit(X_train, y_train)
```

Out[35]:
```
▾ LogisticRegression
LogisticRegression()
```

Model evaluation

In [38]:
```
ypred = lr.predict(X_test)

print ("The accuracy of model is : ", accuracy_score(y_test, ypred))
print()
print("Precision score for model is :", precision_score(y_test, ypred))
print()
print("Recall score for model is :", recall_score(y_test, ypred))
print()
print("f1 score for model is :", f1_score(y_test, ypred))
```

```
The accuracy of model is :  0.7727272727272727

Precision score for model is : 0.6470588235294118

Recall score for model is : 0.8

f1 score for model is : 0.7154471544715447
```