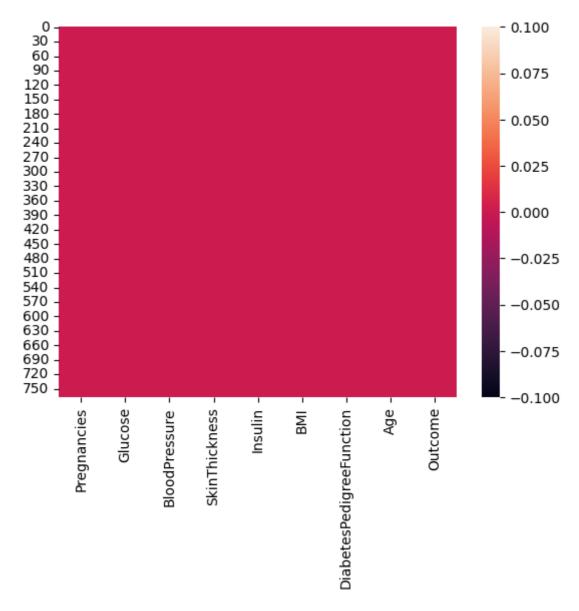
```
In [ ]:
         # Basic Libraries
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         import plotly.express as px
         # ML Libraries
         from sklearn.model_selection import train_test_split
         from sklearn.ensemble import VotingClassifier
         from sklearn.linear_model import LogisticRegression
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.neural_network import MLPClassifier
         # Confusion Matrix Library
         from sklearn import metrics
         from sklearn.metrics import accuracy_score
         from sklearn.metrics import f1_score
         from sklearn.metrics import roc_curve
In [ ]:
         data = pd.read_csv('diabetes.csv')
In [ ]:
         data.head()
           Pregnancies Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction
Out[ ]:
        0
                                                                 33.6
                                                                                              50
                    6
                          148
                                         72
                                                      35
                                                                                       0.627
                                                              0
        1
                    1
                           85
                                         66
                                                      29
                                                                 26.6
                                                                                       0.351
                                                                                              31
        2
                    8
                                                                 23.3
                          183
                                         64
                                                       0
                                                              0
                                                                                       0.672
                                                                                              32
        3
                    1
                           89
                                         66
                                                      23
                                                             94
                                                                 28.1
                                                                                       0.167
                                                                                              21
                    0
                          137
                                         40
                                                      35
                                                            168 43.1
                                                                                       2.288
                                                                                              33
In [ ]:
         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
                                        768 non-null
             Insulin
                                                         int64
         5
                                        768 non-null
                                                         float64
             BMI
         6
             DiabetesPedigreeFunction 768 non-null
                                                         float64
         7
                                        768 non-null
                                                         int64
                                        768 non-null
         8
             Outcome
                                                         int64
        dtypes: float64(2), int64(7)
        memory usage: 54.1 KB
```

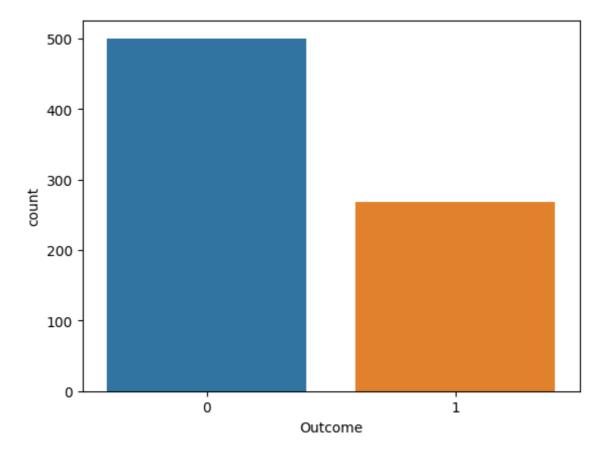
```
In [ ]:
          data.describe()
Out[]:
                Pregnancies
                                Glucose BloodPressure SkinThickness
                                                                         Insulin
                                                                                       BMI DiabetesPedig
                  768.000000 768.000000
                                            768.000000
                                                          768.000000
                                                                      768.000000
                                                                                 768.000000
         count
                    3.845052
                             120.894531
                                             69.105469
                                                           20.536458
                                                                       79.799479
                                                                                  31.992578
         mean
                   3.369578
                              31.972618
                                             19.355807
                                                           15.952218 115.244002
                                                                                   7.884160
            std
           min
                   0.000000
                               0.000000
                                              0.000000
                                                            0.000000
                                                                        0.000000
                                                                                   0.000000
           25%
                                             62.000000
                                                            0.000000
                    1.000000
                              99.000000
                                                                        0.000000
                                                                                  27.300000
           50%
                    3.000000 117.000000
                                             72.000000
                                                           23.000000
                                                                       30.500000
                                                                                  32.000000
           75%
                   6.000000 140.250000
                                             80.000000
                                                           32.000000
                                                                     127.250000
                                                                                  36.600000
           max
                   17.000000 199.000000
                                            122.000000
                                                           99.000000 846.000000
                                                                                  67.100000
In [ ]:
          data.shape
         (768, 9)
Out[ ]:
In [ ]:
          data.isnull().sum()
         Pregnancies
                                         0
Out[ ]:
         Glucose
                                         0
         BloodPressure
                                         0
         SkinThickness
                                         0
         Insulin
                                         0
         BMI
                                         0
         DiabetesPedigreeFunction
                                         0
                                         0
         Age
         Outcome
                                         0
         dtype: int64
In [ ]:
          sns.heatmap(data.isnull())
```

Out[]: <Axes: >



No Null Values Spotted

```
In [ ]:
         data.duplicated().sum()
Out[]: 0
        No Duplicated Values Spotter
In [ ]:
         data.skew()
        Pregnancies
                                      0.901674
Out[]:
         Glucose
                                      0.173754
         BloodPressure
                                     -1.843608
         SkinThickness
                                      0.109372
         Insulin
                                      2.272251
                                     -0.428982
         DiabetesPedigreeFunction
                                      1.919911
        Age
                                      1.129597
         Outcome
                                      0.635017
         dtype: float64
In [ ]:
         sns.countplot(x='Outcome',data=data)
         plt.show()
```



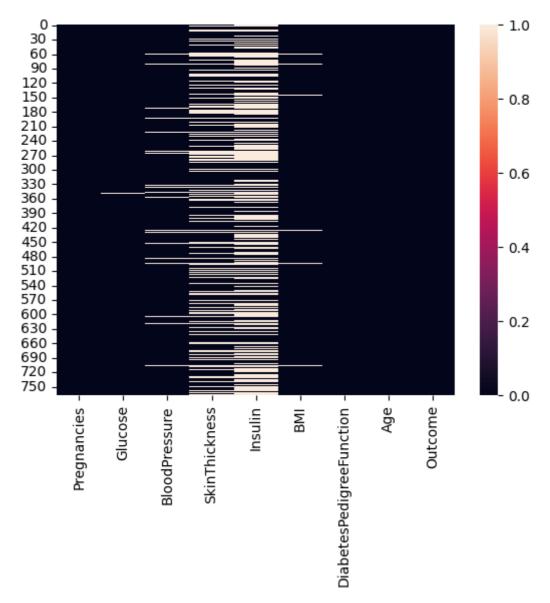
Now We will Convert the Values which are 0 in the columns to Nan (Null Values)

```
In [ ]:
         data_copy = data.copy(deep = True)
         data_copy[['Glucose','BloodPressure','SkinThickness','Insulin','BMI']] = data_copy[[
         ## showing the count of Nans
         print(data_copy.isnull().sum())
        Pregnancies
                                       0
        Glucose
                                       5
        BloodPressure
                                      35
        SkinThickness
                                     227
        Insulin
                                     374
        BMI
                                      11
        DiabetesPedigreeFunction
                                       0
                                       0
        Age
        Outcome
        dtype: int64
        Check Null Values
In [ ]:
         data_copy.isnull().sum()
Out[]: Pregnancies
                                       0
        Glucose
                                       5
        BloodPressure
                                      35
        SkinThickness
                                     227
        Insulin
                                     374
        BMI
                                      11
        DiabetesPedigreeFunction
                                       0
                                       0
        Age
                                       0
        Outcome
```

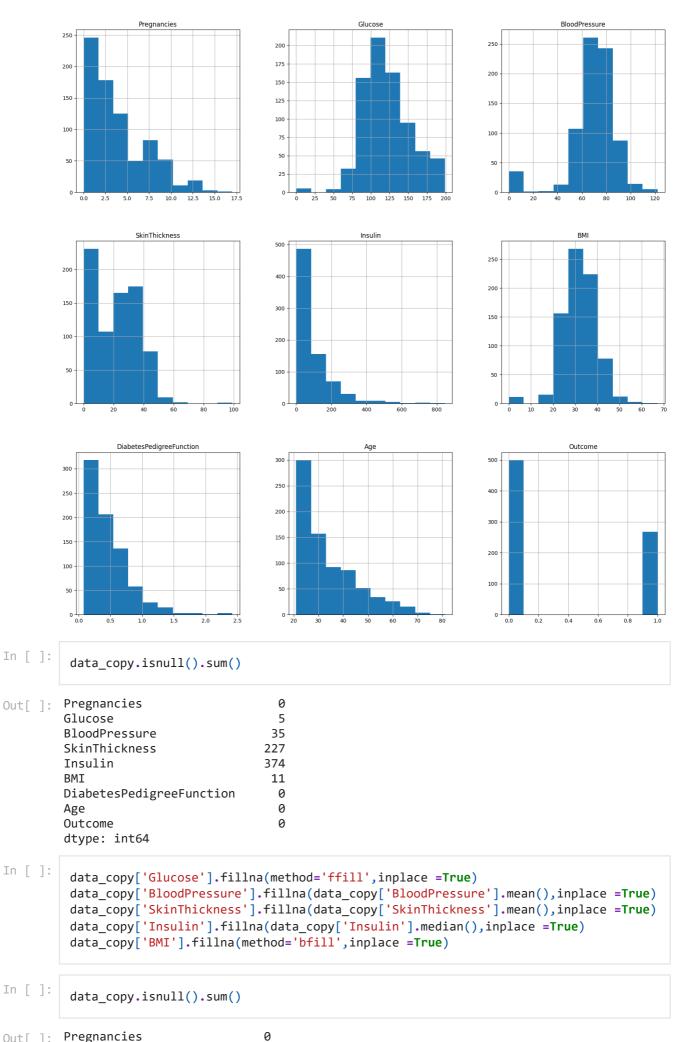
dtype: int64

```
In [ ]: sns.heatmap(data_copy.isnull())
```

```
Out[]: <Axes: >
```



```
In [ ]: data.hist(figsize = (20,20))
Out[ ]: array([[<Axes: title={'center': 'Pregnancies'}>.
```



Out[]: Pregnancies 0 Glucose 0

```
BloodPressure 0
SkinThickness 0
Insulin 0
BMI 0
DiabetesPedigreeFunction 0
Age 0
Outcome 0
dtype: int64
```

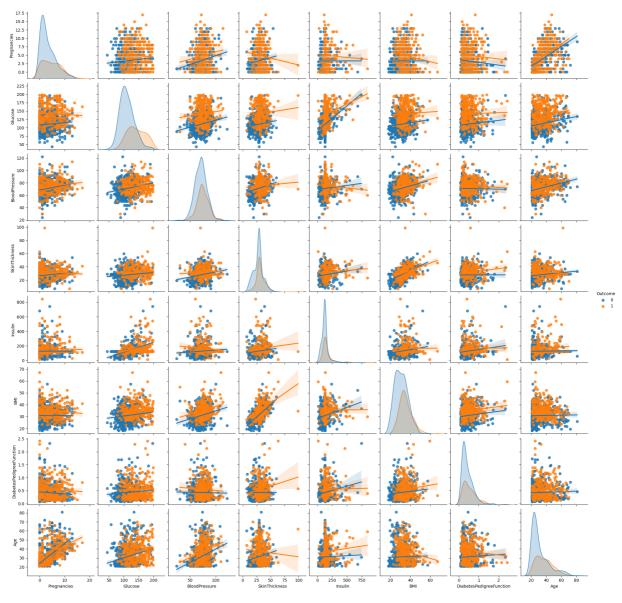
All the Null Values which we added in the place of "0" are now Filled.

```
In [ ]:
           data_copy.hist(figsize = (20,20))
BloodPressure
                      Pregnancies
                                                           Glucose
          250
          200
                                                                                200
                                             120
                                             100
          150
                                                                                150
          100
                                                                                100
                           10.0
                              12.5
                      SkinThickness
                                                           Insulin
                                                                                               вмі
          350
          300
          250
          200
                                                                                100
                                                                                 50
                   DiabetesPedigreeFunction
                                                                                             Outcome
                                             300
          300
                                                                                400
          200
                                                                                300
          150
          100
                                                                                100
In [ ]:
           sns.pairplot(data)
```

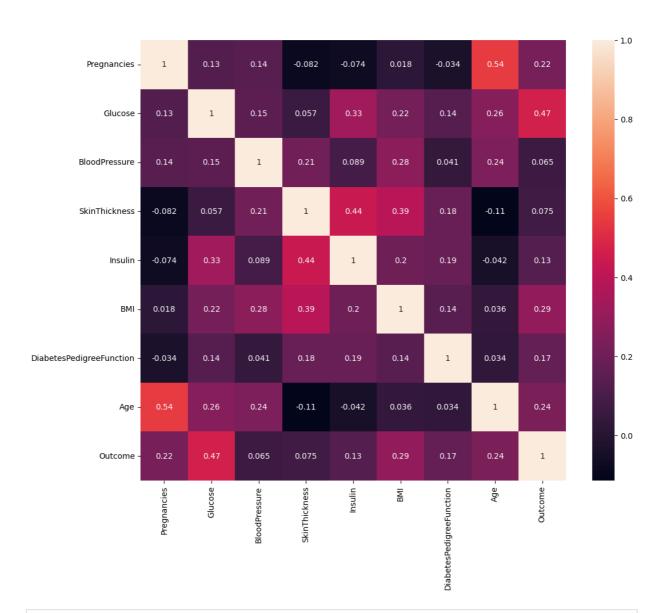
Out[]: <seaborn.axisgrid.PairGrid at 0x1f696d86bd0>



In []:
 sns.pairplot(data=data_copy,hue='Outcome',diag_kind='kde', kind="reg")
 plt.show()



```
In [ ]: plt.figure(figsize=(12,10))
    ax = sns.heatmap(data.corr(),annot = True)
```



Out[]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunct
	0	0.639947	0.868061	-0.033518	6.655021e-01	-0.181541	0.166964	0.468
	1	-0.844885	-1.196747	-0.529859	-1.746338e-02	-0.181541	-0.848188	-0.365
	2	1.233880	2.015177	-0.695306	8.087936e-16	-0.181541	-1.326759	0.604
	3	-0.844885	-1.065648	-0.529859	-7.004289e-01	-0.540642	-0.630655	-0.920
	4	-1.141852	0.507539	-2.680669	6.655021e-01	0.316566	1.544669	5.484
	4)
In []:	у	= data_copy	y.Outcome					
In []:	x	_train,x_te	st,y_trai	n,y_test = tr	ain_test_spli	t(x,y,tes	t_size=1/	3,random_state=42,

Voting Classifier

- A Voting Classifier is a machine learning model that trains on an ensemble of numerous models and predicts an output (class) based on their highest probability of chosen class as the output.
- It simply aggregates the findings of each classifier passed into Voting Classifier and predicts the output class based on the highest majority of voting. The idea is instead of creating separate dedicated models and finding the accuracy for each them, we create a single model which trains by these models and predicts output based on their combined majority of voting for each output class.

```
In [ ]:
         L_R_model = LogisticRegression(solver = 'lbfgs', multi_class='multinomial',random_st
         R_F_model = RandomForestClassifier(n_estimators=100, criterion='gini', max_depth=5,
         KNC_model = KNeighborsClassifier(n_neighbors=10, weights='uniform', algorithm='auto')
         MLP_C_model = MLPClassifier(solver='lbfgs', hidden_layer_sizes=(1000,20), learning_rat
                                     power t=0.4, max iter=250)
         # Voting Classifier
         v_classifier_model = VotingClassifier(estimators=[('LRModel',L_R_model),('RFModel',R
                                                            ('NNModel', MLP_C_model)], voting=
         v_classifier_model.fit(x_train, y_train)
                                             VotingClassifier
Out[]:
               LRModel
                                       RFModel
                                                                KNNModel
                                                                                     NNModel
                               RandomForestClassifier
                                                          KNeighborsClassifier
         LogisticRegression
                                                                                 MLPClassifi
In [ ]:
         #Calculating Details
         print('VotingClassifierModel Train Score is : ' , v_classifier_model.score(x_train,
         print('VotingClassifierModel\ Test\ Score\ is\ :\ '\ ,\ v\_classifier\_model.score(x\_test,\ y\_test))
        VotingClassifierModel Train Score is: 0.93359375
        VotingClassifierModel Test Score is : 0.72265625
       Prediction Calculation
In [ ]:
         y pred = v classifier model.predict(x test)
         print('Predicted Value for VotingClassifierModel is : ' , y_pred[:10])
```

Predicted Value for VotingClassifierModel is : [0 1 0 0 0 0 1 1 0 0]

Out[]: array([0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0,

Predictions

y pred

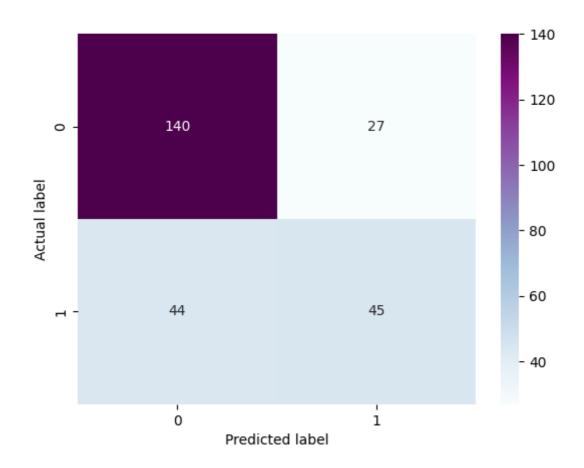
In []:

Confusion Matrix

```
confusion_matrix = metrics.confusion_matrix(y_test, y_pred)
p = sns.heatmap(pd.DataFrame(confusion_matrix), annot=True, cmap="BuPu" ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[]: Text(0.5, 23.522222222222, 'Predicted label')

Confusion matrix



Calculating Accuracy

```
# Precision : measures the percentage of predictions made by the model that are corr
# Recall : measures the percentage of relevant data points that were correctly id
F1Score = f1_score(y_test, y_pred, average='micro') #it can be : binary,macro,weight
print('F1 Score is : ', F1Score)
```

F1 Score is : 0.72265625

VotingClassifierModel ROC curve

