DIABETES PREDICTION SYSTEM

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OBJECTIVE:

To Predict whether a Patient has Diabetes based on certain diagnostic measurements included in the dataset.

Importing Required Libraries

```
In [1]: import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
In [2]: # Loading the dataset
```

Features Description

Pregnancies: No. times pregnant

df =pd.read_csv("diabetes.csv")

Glucose: Plasma glucose concentration a 2 hours in a glucose tolerance test

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**: Diabetes Pedigree function

Age: Age in years

Outcome: Result Yes if "1" or No if "0"

```
In [3]: # Cheking random 10 entries
         df.sample(10)
Out[3]:
               Pregnancies Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age
                        2
                                                                    64 24.7
                                                                                                      21
           94
                               142
                                              82
                                                             18
                                                                                               0.761
                        2
                                                             0
          451
                               134
                                               70
                                                                     0 28.9
                                                                                               0.542
                                                                                                      23
           54
                        7
                               150
                                              66
                                                            42
                                                                   342 34.7
                                                                                               0.718
                                                                                                      42
          411
                                                            30
                                                                                                      25
                                              72
                                                                   176 34.4
                                                                                               0.528
                        1
                               112
          361
                        5
                                              70
                                                             0
                                                                     0 29.8
                                                                                               0.207
                               158
                                                                                                      63
          585
                                                                     0 22.5
                                                                                               0.417
                                                                                                      22
                        1
                                93
                                              56
                                                             11
          302
                        5
                                77
                                              82
                                                            41
                                                                    42 35.8
                                                                                               0.156
                                                                                                      35
          100
                        1
                               163
                                              72
                                                             0
                                                                     0 39.0
                                                                                               1.222
                                                                                                      33
          630
                        7
                               114
                                               64
                                                             0
                                                                     0 27.4
                                                                                               0.732
                                                                                                      34
                                                                                               0.717
          530
                        2
                                                             18
                                                                   106 29.8
                               122
                                               60
                                                                                                      22
In [4]:
         # Checking number of Rows and Columns
         df.shape
Out[4]: (768, 9)
In [5]: # Checking basic info about dataset
         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				
<pre>dtypes: float64(2), int64(7)</pre>							

memory usage: 54.1 KB

```
In [6]: # checking missing values
        df.isnull().sum()
Out[6]: Pregnancies
                                    0
        Glucose
                                    0
        BloodPressure
                                    0
        SkinThickness
                                    0
        Insulin
                                    0
                                    0
        DiabetesPedigreeFunction
        Age
                                    0
        Outcome
                                    0
        dtype: int64
```

In [7]: # Checking Basic stats

df.describe().T

Out[7]:

	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
ВМІ	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

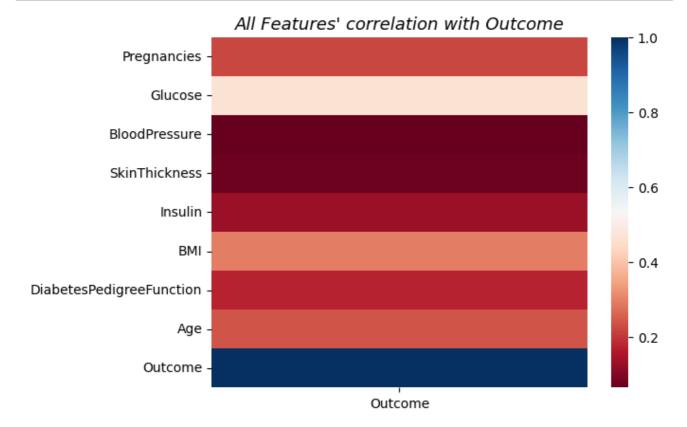
In [8]: # Finding insights aboutIndependent Features with Dependent(Outcome) df.corr()[['Outcome']]

Out[8]:

	Outcome
Pregnancies	0.221898
Glucose	0.466581
BloodPressure	0.065068
SkinThickness	0.074752
Insulin	0.130548
ВМІ	0.292695
DiabetesPedigreeFunction	0.173844
Age	0.238356
Outcome	1.000000

In [9]: # Let's check correlation using heatmap with Dependent Feature i.e. "Outcome"

plt.title("All Features' correlation with Outcome", fontsize=13, fontstyle='italic')
sns.heatmap(df.corr()[['Outcome']], cmap='RdBu')
plt.show()

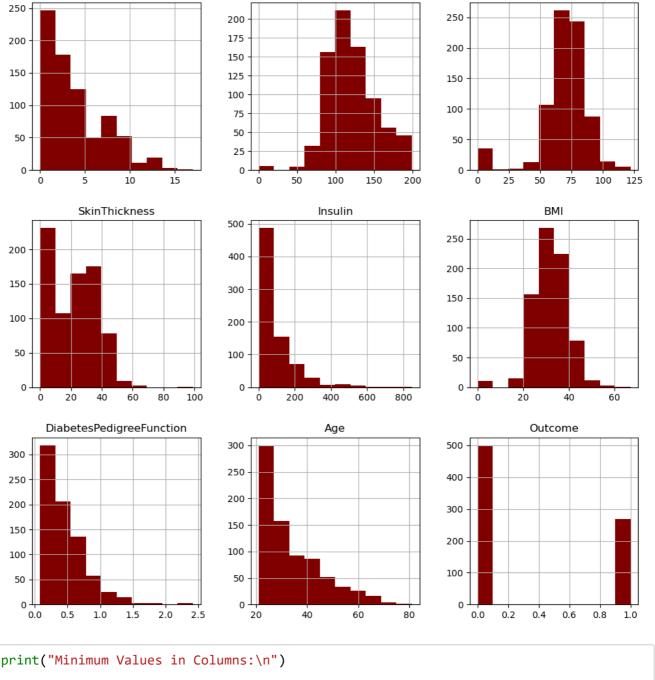


```
In [10]: # Checking Histplot

df.hist(figsize=(12,12),color='Maroon')
plt.show()
```

Glucose

BloodPressure



In [11]: print("Minimum Values in Columns:\n") for i in df.columns: x=df[i].min() print(i,x)

Minimum Values in Columns:

Pregnancies

Pregnancies 0
Glucose 0
BloodPressure 0
SkinThickness 0
Insulin 0
BMI 0.0
DiabetesPedigreeFunction 0.078
Age 21
Outcome 0

Here, we can observe that 0 in certain columns does not make sense in real time. So,we will chnage that 0 with average value

'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI'

```
In [12]:
         Glu = df.Glucose.mean()
         Bld =df.BloodPressure.mean()
         Ski =df.SkinThickness.mean()
         Ins = df.Insulin.mean()
         Bmi = df.BMI.mean()
         print(f"Average of Glucose is: {Glu}")
         print(f"Average of BloodPressure is: {Bld}")
         print(f"Average of SkinThickness is: {Ski}")
         print(f"Average of Insulin is: {Ins}")
         print(f"Average of BMI is: {Bmi}")
         Average of Glucose is: 120.89453125
         Average of BloodPressure is: 69.10546875
         Average of SkinThickness is: 20.536458333333332
         Average of Insulin is: 79.79947916666667
         Average of BMI is: 31.992578124999998
```

Let's make new dataframe and then modify as per requirements.

```
In [13]:
           new df =df.copy()
           new_df.head()
In [14]:
Out[14]:
               Pregnancies Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age O
            0
                         6
                                 148
                                                 72
                                                                35
                                                                         0
                                                                            33.6
                                                                                                     0.627
                                                                                                             50
            1
                         1
                                                                29
                                  85
                                                 66
                                                                            26.6
                                                                                                     0.351
                                                                                                             31
                         8
            2
                                 183
                                                 64
                                                                 0
                                                                         0
                                                                            23.3
                                                                                                     0.672
                                                                                                             32
            3
                         1
                                  89
                                                 66
                                                                23
                                                                            28.1
                                                                                                             21
                                                                        94
                                                                                                     0.167
            4
                         n
                                                 40
                                                                       168 43.1
                                                                                                     2.288
                                                                                                             33
                                 137
                                                                35
```

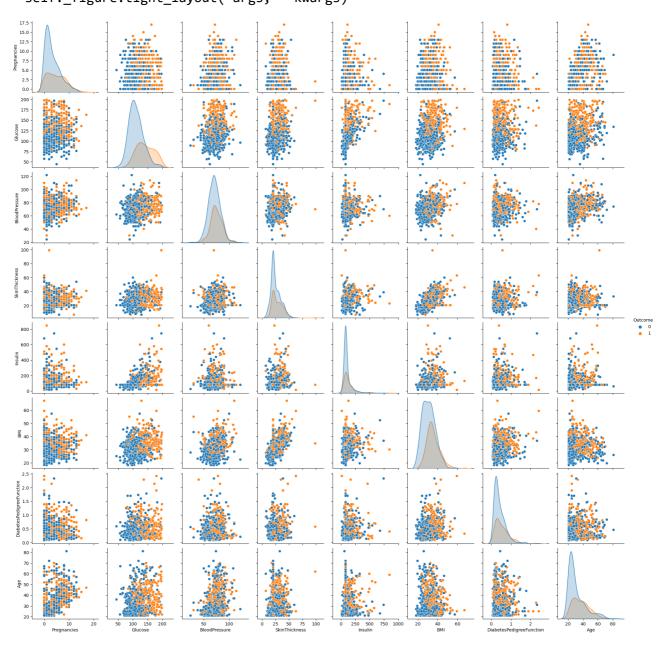
We will now chnage 0 with average value in respective columns.

```
In [15]: new_df['Glucose']= new_df['Glucose'].replace(0,Glu)
    new_df['BloodPressure']= new_df['BloodPressure'].replace(0,Bld)
    new_df['SkinThickness']= new_df['SkinThickness'].replace(0,Ski)
    new_df['Insulin']= new_df['Insulin'].replace(0,Ins)
    new_df['BMI']= new_df['BMI'].replace(0.00,Bmi)
```

Glucose 44.0 BloodPressure 24.0 SkinThickness 7.0 Insulin 14.0 BMI 18.2

```
In [17]: sns.pairplot(new_df,hue="Outcome")
   plt.show()
```

C:\Users\PRATYAKSH\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning:
The figure layout has changed to tight
 self._figure.tight_layout(*args, **kwargs)



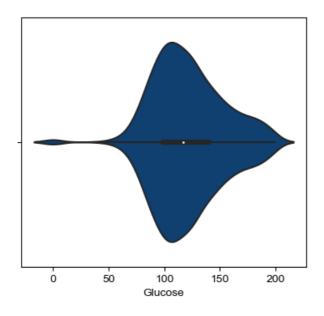
```
In [18]: fig,axes = plt.subplots(1,2,figsize=(10,4),squeeze=False)
    plt.suptitle("Glucose Before and after Correction",fontsize=15)

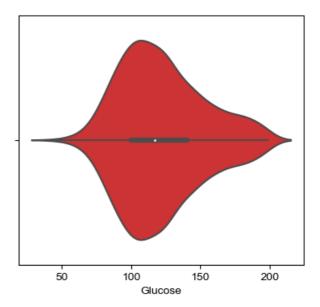
    sns.set(style='whitegrid')

    sns.violinplot(ax = axes[0,0], x=df.Glucose, data=df,palette='ocean')
    sns.violinplot(ax = axes[0,1], x=new_df.Glucose, data=new_df,palette='Set1')

    plt.show()
```

Glucose Before and after Correction

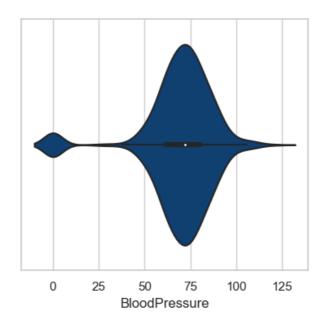


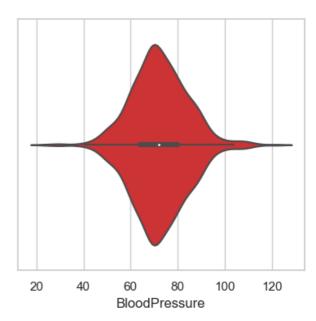


```
In [19]: fig,axes = plt.subplots(1,2,figsize=(10,4),squeeze=False)
    plt.suptitle("Blood Pressure Before and after Correction",fontsize=15)
    sns.set(style='whitegrid')

sns.violinplot(ax = axes[0,0], x=df.BloodPressure, data=df,palette='ocean')
    sns.violinplot(ax = axes[0,1], x=new_df.BloodPressure, data=new_df,palette='Set1')
    plt.show()
```

Blood Pressure Before and after Correction





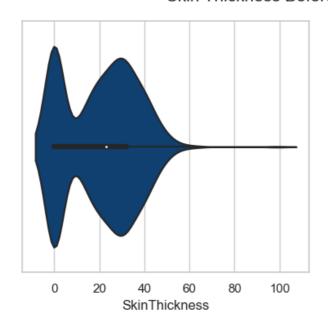
```
In [20]: fig,axes = plt.subplots(1,2,figsize=(10,4),squeeze=False)
    plt.suptitle("Skin Thickness Before and after Correction",fontsize=15)

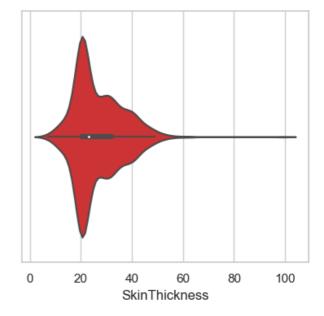
    sns.set(style='whitegrid')

    sns.violinplot(ax = axes[0,0], x=df.SkinThickness, data=df,palette='ocean')
    sns.violinplot(ax = axes[0,1], x=new_df.SkinThickness, data=new_df,palette='Set1')

    plt.show()
```

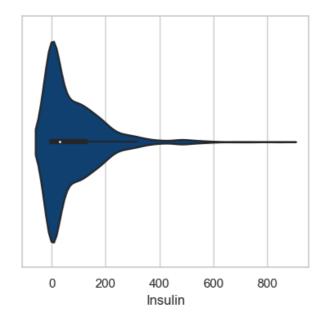
Skin Thickness Before and after Correction

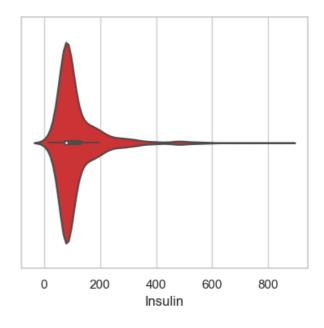




```
In [21]: fig,axes = plt.subplots(1,2,figsize=(10,4),squeeze=False)
    plt.suptitle("Insulin Before and after Correction",fontsize=15)
    sns.set(style='whitegrid')
    sns.violinplot(ax = axes[0,0], x=df.Insulin, data=df,palette='ocean')
    sns.violinplot(ax = axes[0,1], x=new_df.Insulin, data=new_df,palette='Set1')
    plt.show()
```

Insulin Before and after Correction





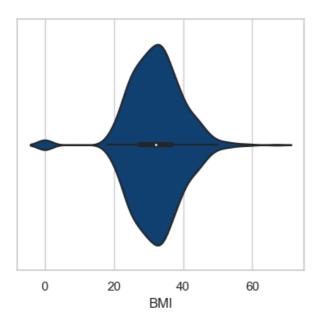
```
In [22]: fig,axes = plt.subplots(1,2,figsize=(10,4),squeeze=False)
    plt.suptitle("BMI Before and after Correction",fontsize=15)

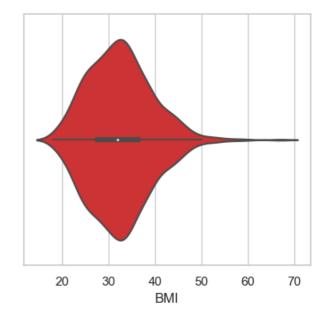
    sns.set(style='whitegrid')

    sns.violinplot(ax = axes[0,0], x=df.BMI, data=df,palette='ocean')
    sns.violinplot(ax = axes[0,1], x=new_df.BMI, data=new_df,palette='Set1')

    plt.show()
```

BMI Before and after Correction





Let's work on Machine learning model to Predict Outcome

```
In [23]: # Features selection

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

```
In [24]: # To split data into train and test
    from sklearn.model_selection import train_test_split
    X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2, random_state=16)
```

```
In [25]: # Using Logistic Regression model
         from sklearn.linear_model import LogisticRegression
         model =LogisticRegression(random_state=16)
         model.fit(X_train,y_train)
         C:\Users\PRATYAKSH\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:46
         0: ConvergenceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-lear
         n.org/stable/modules/preprocessing.html)
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (h
         ttps://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)
           n_iter_i = _check_optimize_result(
Out[25]:
                   LogisticRegression
          LogisticRegression(random_state=16)
In [26]: |y_pred = model.predict(X_test)
In [27]: # import the metrics class
         from sklearn import metrics
         cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
         cnf_matrix
Out[27]: array([[94, 8],
                 [21, 31]], dtype=int64)
In [28]: | from sklearn.metrics import classification_report
         target_names = ['Diabetes Not Detected', 'Diabetes Detected']
         print(classification_report(y_test, y_pred, target_names=target_names))
                                 precision
                                              recall f1-score
                                                                 support
         Diabetes Not Detected
                                                0.92
                                     0.82
                                                          0.87
                                                                     102
             Diabetes Detected
                                     0.79
                                                0.60
                                                          0.68
                                                                      52
                                                          0.81
                                                                     154
                      accuracy
                                                          0.77
                     macro avg
                                    0.81
                                               0.76
                                                                     154
                                     0.81
                                                0.81
                                                          0.80
                                                                     154
                  weighted avg
In [29]: # Checking accuracy of the model
         from sklearn.metrics import accuracy_score
         accuracy = accuracy_score(y_pred,y_test)
         print(f"Accuracy of the model is: {accuracy*100}")
```

Accuracy of the model is: 81.16883116883116

Thank You

GitHub Link:

https://github.com/ipratyaksh21/DIABETES-PREDICTION-FROM-MERISKILL-INTERNSHIP.git