```
**About Dataset**
```

\*Dependent Column: \* Outcome (1: diabetic Patient, 0: Non-diabetic patient)

Pregnancies Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age

Aim of the Project : Can you build a model (Machine learning or deep learning ) to accurately predict whether or not the patients in the dataset have diabetes or not?

```
#Normal Library
import numpy as np
import pandas as pd
#Visulization Library
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set()
#Warning library
import warnings
warnings.filterwarnings('ignore')
#anova testing
import scipy.stats as stats
#scaling the data
from sklearn.preprocessing import StandardScaler
#Train Test split
from sklearn.model_selection import train_test_split
#ML model - regeression
from sklearn.linear_model import LinearRegression
#ML model - regeression - Performance matrix
from sklearn import metrics
from sklearn.metrics import r2_score,mean_absolute_percentage_error, mean_squared_error
#ML model - Classification
#ML model - Classification - Performance matrix
from sklearn import metrics
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score, roc_auc_score
#Improve the accuracy
from sklearn.model_selection import cross_val_score
df= pd.read_csv(r"/content/diabetes.csv")
df.head()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunctio
0	6	148	72	35	0	33.6	0.62
1	1	85	66	29	0	26.6	0.35
2	8	183	64	0	0	23.3	0.67
3	1	89	66	23	94	28.1	0.16
4	0	137	40	35	168	43.1	2.28

df.info()

<sup>\*</sup>Independent Columns(8): \*

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
                             Non-Null Count Dtype
    Column
---
    -----
0
    Pregnancies
                             768 non-null
                                             int64
1
    Glucose
                             768 non-null
                                             int64
    BloodPressure
                            768 non-null
                                             int64
    SkinThickness
                             768 non-null
                                             int64
                            768 non-null
 4
    Insulin
                                             int64
                             768 non-null
                                             float64
    DiabetesPedigreeFunction 768 non-null
                                             float64
                             768 non-null
                                             int64
    Age
                             768 non-null
8
    Outcome
                                             int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

### **Checking Duplicate rows**

```
def drop_dup(df):
    if df.duplicated().any() == True:
        df.drop_duplicates(inplace= True, Keep = "Last",reset_index = True)
        print("Data after removing duplicates row :" , df.dupdated().sum())
    else:
        return "No action required( No duplicate found)"

drop_dup(df)
    'No action required( No duplicate found)'
```

#### **Checking Null Values**

```
print(df.isnull().sum())
print("****")
print(df.isnull().sum()/len(df)*100)
     Pregnancies
     Glucose
     BloodPressure
                                 0
     SkinThickness
                                 0
     Insulin
     BMI
     DiabetesPedigreeFunction
     Outcome
     dtype: int64
     Pregnancies
     Glucose
     BloodPressure
                                 0.0
     SkinThickness
                                 0.0
     Insulin
                                 0.0
     BMT
                                 0.0
     {\tt DiabetesPedigreeFunction}
                                 0.0
                                 0.0
     Outcome
                                 0.0
     dtype: float64
```

# Check unique counts

```
def check_unique_count(df):
 unique_counts = df.nunique()
 print(unique_counts)
check_unique_count(df)
     Pregnancies
     Glucose
                                 136
     BloodPressure
                                 47
     SkinThickness
                                  51
     Insulin
                                 186
     RMT
                                 248
     DiabetesPedigreeFunction
                                 517
                                  52
     Outcome
                                   2
     dtype: int64
```

## Check unique counts data entry in columns

```
9/13/23, 12:31 PM
                                                                  Biabetic Dataset.ipynb - Colaboratory
   for i in df.columns:
     print(i)
     print("*****")
     print(set(df[i].tolist()))
     print("__
        Pregnancies
        {0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17}
        Glucose
         {0, 44, 56, 57, 61, 62, 65, 67, 68, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94,
        BloodPressure
        {0, 24, 30, 38, 40, 44, 46, 48, 50, 52, 54, 55, 56, 58, 60, 61, 62, 64, 65, 66, 68, 70, 72, 74, 75, 76, 78, 80, 82, 84, 85, 86, 88,
        SkinThickness
        {0, 7, 8, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 4
        Insulin
         {0, 14, 15, 16, 18, 22, 23, 25, 540, 29, 543, 32, 545, 36, 37, 38, 40, 41, 42, 43, 44, 45, 46, 48, 49, 50, 51, 52, 53, 54, 55, 56,
        {0.0, 37.3, 18.4, 19.9, 19.4, 19.6, 22.2, 23.3, 24.4, 23.2, 25.8, 27.6, 27.4, 28.0, 28.9, 28.6, 32.8, 29.0, 29.7, 26.6, 27.1, 28.1,
        DiabetesPedigreeFunction
         {0.351, 0.484, 1.189, 0.375, 0.875, 0.851, 0.665, 1.101, 1.476, 0.391, 1.391, 2.42, 0.398, 0.828, 0.218, 0.101, 0.226, 0.234, 0.21,
        {21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53
        Outcome
         {0, 1}
        4
    data analysized: columns -['Glucose', 'BloodPressure', 'SkinThickness"Insulin', 'BMI'] has value 0 which is wrong.
   Consider null values = ['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI']
   for col in Consider_null_values:
     df[col].replace(0, np.nan, inplace=True)
   df.isnull().sum()
        Pregnancies
                                       0
         Glucose
                                       5
        BloodPressure
                                      35
        SkinThickness
                                     227
        Insulin
                                     374
                                      11
```

BMI  ${\tt DiabetesPedigreeFunction}$ 0 Age 0 Outcome a dtype: int64

df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 768 entries, 0 to 767 Data columns (total 9 columns):

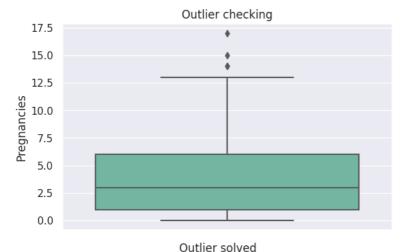
#	Column	Non-Null Count	Dtype
0	Pregnancies	768 non-null	int64
1	Glucose	763 non-null	float64
2	BloodPressure	733 non-null	float64
3	SkinThickness	541 non-null	float64
4	Insulin	394 non-null	float64
5	BMI	757 non-null	float64
6	DiabetesPedigreeFunction	768 non-null	float64
7	Age	768 non-null	int64
8	Outcome	768 non-null	int64
dtvn	es: float64(6), int64(3)		

memory usage: 54.1 KB

```
#Using imputer method to fill the values.
df["Glucose"] = df["Glucose"].fillna(df["Glucose"].median())
df["BloodPressure"] = df["BloodPressure"].fillna(df["BloodPressure"].median())
df["SkinThickness"] = df["SkinThickness"].fillna(df["SkinThickness"].median())
df["Insulin"] = df["Insulin"].fillna(df["Insulin"].median())
df["BMI"] = df["BMI"].fillna(df["BMI"].median())
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
                     Glucose
                                                                          768 non-null
                                                                                                          float64
                     BloodPressure
                                                                         768 non-null
                                                                                                          float64
                     SkinThickness
                                                                          768 non-null
                                                                                                          float64
                    Insulin
                                                                         768 non-null
                                                                                                          float64
                    BMI
                                                                                                          float64
             5
                                                                         768 non-null
                                                                                                          float64
             6
                   DiabetesPedigreeFunction 768 non-null
                    Age
                                                                         768 non-null
                                                                                                          int64
            8
                   Outcome
                                                                         768 non-null
                                                                                                          int64
          dtypes: float64(6), int64(3)
           memory usage: 54.1 KB
for i in df.columns:
    print(i)
    print("*****")
    print(set(df[i].tolist()))
    print("_
           Pregnancies
           {0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17}
          Glucose
          {44.0, 56.0, 57.0, 61.0, 62.0, 65.0, 67.0, 68.0, 71.0, 72.0, 73.0, 74.0, 75.0, 76.0, 77.0, 78.0, 79.0, 80.0, 81.0, 82.0, 83.0, 84.0
          BloodPressure
           {24.0, 30.0, 38.0, 40.0, 44.0, 46.0, 48.0, 50.0, 52.0, 54.0, 55.0, 56.0, 58.0, 60.0, 61.0, 62.0, 64.0, 65.0, 66.0, 68.0, 70.0, 72.0
          SkinThickness
           {7.0, 8.0, 10.0, 11.0, 12.0, 13.0, 14.0, 15.0, 16.0, 17.0, 18.0, 19.0, 20.0, 21.0, 22.0, 23.0, 24.0, 25.0, 26.0, 27.0, 28.0, 29.0,
           Insulin
           {14.0, 15.0, 16.0, 18.0, 22.0, 23.0, 25.0, 540.0, 29.0, 543.0, 32.0, 545.0, 36.0, 37.0, 38.0, 40.0, 41.0, 42.0, 43.0, 44.0, 45.0, 43.0, 44.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.0, 45.
          RMT
           ****
           {37.3, 18.4, 19.9, 19.4, 19.6, 22.2, 23.3, 24.4, 23.2, 25.8, 27.6, 27.4, 28.0, 28.9, 28.6, 32.8, 29.0, 29.7, 26.6, 27.1, 28.1, 30.1
          DiabetesPedigreeFunction
           {0.351, 0.484, 1.189, 0.375, 0.875, 0.851, 0.665, 1.101, 1.476, 0.391, 1.391, 2.42, 0.398, 0.828, 0.218, 0.101, 0.226, 0.234, 0.21,
          Age
           {21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53
          Outcome
           {0, 1}
          4
```

#### **Outliers Check -**

```
#column name - Pregnancies as Preg
plt.figure(figsize=(14,4))
plt.subplot(121)
sns.boxplot(y = "Pregnancies", data = df, palette ='Set2')
plt.title("Outlier checking")
```



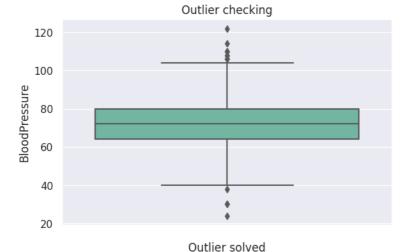


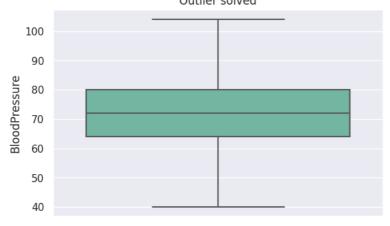
```
#column name - Glucose as Glu
plt.figure(figsize=(14,4))
plt.subplot(121)
sns.boxplot(y = "Glucose", data = df, palette ='Set2' )
plt.title("Outlier checking")
```

# \*

plt.show()

```
Outlier checking
        200
        180
        160
#column name - BloodPressure as blood
plt.figure(figsize=(14,4))
plt.subplot(121)
sns.boxplot(y = "BloodPressure", data = df, palette ='Set2' )
plt.title("Outlier checking")
blood_q1 = df['BloodPressure'].quantile(0.25)
blood_q3 = df['BloodPressure'].quantile(0.75)
blood_iqr = blood_q3 - blood_q1
blood_upper = blood_q3 + 1.5 * blood_iqr
blood_lower = blood_q1 - 1.5 * blood_iqr
df['BloodPressure'] = np.where(df['BloodPressure'] > blood_upper,blood_upper,
                                  np.where(df['BloodPressure'] < blood_lower, blood_lower,</pre>
                                        df['BloodPressure']) )
plt.figure(figsize=(14,4))
plt.subplot(122)
sns.boxplot(y = "BloodPressure", data = df, palette ='Set2')
plt.title("Outlier solved")
plt.show()
```



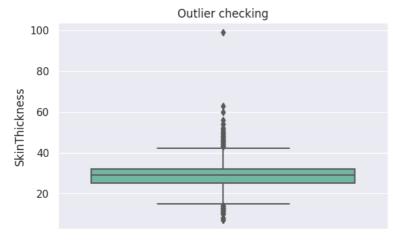


```
#Column SkinThickness as Skin

plt.figure(figsize=(14,4))
plt.subplot(121)
sns.boxplot(y = "SkinThickness", data = df, palette ='Set2')
plt.title("Outlier checking")

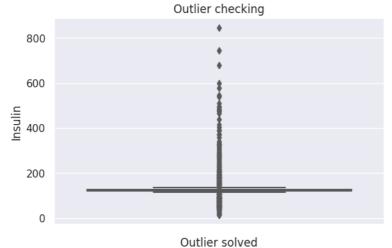
#########################

Skin_q1 = df['SkinThickness'].quantile(0.25)
Skin_q3 = df['SkinThickness'].quantile(0.75)
```





```
# Column Insulin as Insulin
plt.figure(figsize=(14,4))
plt.subplot(121)
sns.boxplot(y = "Insulin", data = df, palette ='Set2' )
plt.title("Outlier checking")
Insulin_q1 = df['Insulin'].quantile(0.25)
Insulin_q3 = df['Insulin'].quantile(0.75)
Insulin_iqr = Insulin_q3 -Insulin_q1
Insulin_upper = Insulin_q3 + 1.5 * Insulin_iqr
Insulin_lower = Insulin_q1 - 1.5 * Insulin_iqr
df['Insulin'] = np.where(df['Insulin'] > Insulin_upper,Insulin_upper,
                                 np.where(df['Insulin'] < Insulin_lower, Insulin_lower,</pre>
                                        df['Insulin']) )
plt.figure(figsize=(14,4))
plt.subplot(122)
sns.boxplot(y = "Insulin", data = df, palette ='Set2')
plt.title("Outlier solved")
plt.show()
```



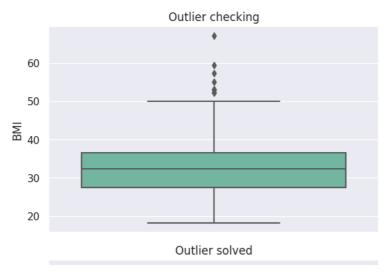


### # Column BMI

plt.figure(figsize=(14,4))

#### 

```
plt.figure(figsize=(14,4))
plt.subplot(122)
sns.boxplot(y = "BMI", data = df, palette ='Set2')
plt.title("Outlier solved")
plt.show()
```



#### # column - DiabetesPedigreeFunction

```
plt.figure(figsize=(14,4))
plt.subplot(121)
sns.boxplot(y = "DiabetesPedigreeFunction", data = df, palette ='Set2')
plt.title("Outlier checking")
```

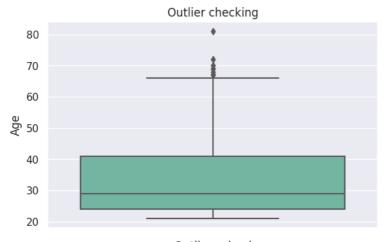
#### 

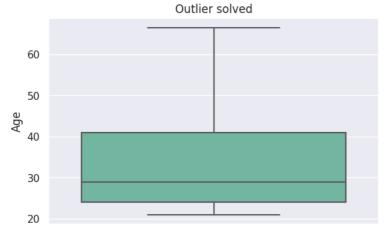
```
DiabetesPedigreeFunction_q1 = df['DiabetesPedigreeFunction'].quantile(0.25)
DiabetesPedigreeFunction_q3 = df['DiabetesPedigreeFunction'].quantile(0.75)
DiabetesPedigreeFunction_iqr = DiabetesPedigreeFunction_q3 -DiabetesPedigreeFunction_q1
DiabetesPedigreeFunction_upper = DiabetesPedigreeFunction_q3 + 1.5 * DiabetesPedigreeFunction_iqr
DiabetesPedigreeFunction_lower = DiabetesPedigreeFunction_q1 - 1.5 * DiabetesPedigreeFunction_iqr
```

## 

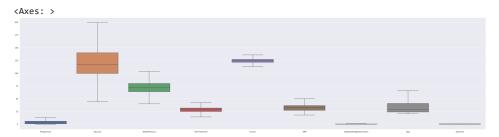
```
plt.figure(figsize=(14,4))
plt.subplot(122)
sns.boxplot(y = "DiabetesPedigreeFunction", data = df, palette ='Set2')
plt.title("Outlier solved")
plt.show()
```

```
Outlier checking
        2.5
#Column - Age
plt.figure(figsize=(14,4))
plt.subplot(121)
sns.boxplot(y = "Age", data = df, palette ='Set2' )
plt.title("Outlier checking")
Age_q1 = df['Age'].quantile(0.25)
Age_q3 = df['Age'].quantile(0.75)
Age_iqr = Age_q3 - Age_q1
Age_upper = Age_q3 + 1.5 * Age_iqr
Age_lower = Age_q1 - 1.5 * Age_iqr
df['Age'] = np.where(df['Age'] > Age_upper,Age_upper,
                                 np.where(df['Age'] < Age_lower, Age_lower,</pre>
                                       df['Age']) )
plt.figure(figsize=(14,4))
plt.subplot(122)
sns.boxplot(y = "Age", data = df, palette ='Set2')
plt.title("Outlier solved")
plt.show()
```





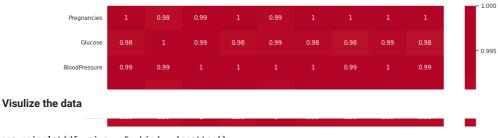
plt.figure(figsize=(50,12))
sns.boxplot(df)



### Normal Distribution checkSkewenss Check\*\*\*

### Finding correlation it is not required for clinical dataset but just t see the graph

```
plt.figure(figsize=(15,8))
corr = df.describe().corr()
sns.heatmap(corr, annot=True, cmap='coolwarm',center = 0)
plt.show()
```



sns.pairplot(df, size = 5, kind = 'scatter')
plt.show()



Pair plot is indicating to use logistic classification model

pip install movecolumn

Requirement already satisfied: movecolumn in /usr/local/lib/python3.10/dist-packages (0.0.7)

- Hittia Control - See Andre Control - Charles For the Control - Carren Market - Market - Carren Market - Carren - Carre

import movecolumn as mc
mc.MoveToLast(df,'Outcome')

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunct
0	6.0	148.0	72.0	35.0	125.000	33.6	0.
1	1.0	85.0	66.0	29.0	125.000	26.6	0.
2	8.0	183.0	64.0	29.0	125.000	23.3	0.
3	1.0	89.0	66.0	23.0	112.875	28.1	0.
4	0.0	137.0	40.0	35.0	135.875	43.1	1.
763	10.0	101.0	76.0	42.5	135.875	32.9	0.
764	2.0	122.0	70.0	27.0	125.000	36.8	0.
765	5.0	121.0	72.0	23.0	112.875	26.2	0.
766	1.0	126.0	60.0	29.0	125.000	30.1	0.
767	1.0	93.0	70.0	31.0	125.000	30.4	0.

768 rows × 9 columns

## Spliting train test

```
x = df.iloc[:,0:-1]
y = df['Outcome']
```

## Scailing the dataset

### y.value\_counts()

0 5001 268

Name: Outcome, dtype: int64

# Smote method to handle imbalanced dataset

```
from imblearn.over_sampling import SMOTE
smote = SMOTE()
```

```
x, y = smote.fit_resample(x,y)
y.value_counts()
          500
          500
     Name: Outcome, dtype: int64
#scailing dataset
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
sc_x = sc.fit_transform(x)
pd.DataFrame(sc_x)
variable = sc_x
variable.shape
     (1000, 8)
Split the data into train and test
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(sc_x, y, test_size=0.2, random_state=101)
transform the data through yeo-johnson method
from sklearn.preprocessing import PowerTransformer
pt1 = PowerTransformer(method='yeo-johnson')
x_train_transformed = pt1.fit_transform(x_train)
x_test_transformed = pt1.fit_transform(x_test)
Logistic regeression model
from sklearn.linear_model import LogisticRegression
logistic = LogisticRegression()
logistic.fit(x_train_transformed, y_train)
y_train_transformed_pred = logistic.predict(x_train_transformed)
y test transformed pred = logistic.predict(x test transformed)
print(accuracy_score(y_train, y_train_transformed_pred))
print(accuracy_score(y_test, y_test_transformed_pred))
     0.78125
     0.76
Result: model accuracy without CVS - train(78 %), test (76 %)
#CVS
training_accuracy = cross_val_score(logistic, x_train_transformed, y_train, cv=15)
test_accuracy = cross_val_score(logistic, x_test_transformed, y_test, cv=15)
print(training accuracy[14])
print(test_accuracy[14])
     0.8301886792452831
     0.8461538461538461
Result: model accuracy with CVS - train(83 %), test (84 %)
Performace matrix
print(classification_report(y_train, y_train_transformed_pred))
print(classification_report(y_test, y_test_transformed_pred))
```

```
print("_
print(confusion matrix(y train, y train transformed pred))
print(confusion_matrix(y_test, y_test_transformed_pred))
print("_
                                                                  _")
print(roc_auc_score(y_train, y_train_transformed_pred))
print(roc_auc_score(y_test, y_test_transformed_pred))
                   precision
                                 recall f1-score
                                                    support
                                   0 78
                                             0.79
                0
                         0.79
                                                         409
                1
                         0.77
                                   0.78
                                             0.78
                                                         391
         accuracy
                                             0.78
                                                         800
                         0.78
                                   0.78
                                             0.78
                                                         800
        macro avg
                         0.78
                                   0.78
                                             0.78
                                                         800
     weighted avg
                    precision
                                 recall f1-score
                                                     support
                0
                         0.72
                                   0.77
                                             0.74
                                                          91
                         0.80
                                   0.75
                                             0.77
                                                         109
                1
         accuracy
                                             0.76
                                                         200
        macro avg
                         0.76
                                   0.76
                                             0.76
                                                         200
     weighted avg
                         0.76
                                   0.76
                                             0.76
                                                         200
     [[320 89]
      [ 86 305]]
     [[70 21]
      [27 82]]
     0.7812236194573503
```

0.7607621736062102

0.7857142857142857

KNN Model - Mostly Data scientist used to prefer this model for cinical sector datset

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
knn.fit(x_train_transformed, y_train)
y_train_pred_knn = knn.predict(x_train_transformed)
y_test_pred_knn = knn.predict(x_test_transformed)
accuracy_knn_train = accuracy_score(y_train, y_train_pred_knn)
accuracy_knn_test = accuracy_score(y_test, y_test_pred_knn)
print(accuracy_knn_train)
print(accuracy_knn_test)
     0.8275
     0.76
#CVS
training_accuracy = cross_val_score(knn, x_train_transformed, y_train, cv=15)
test_accuracy = cross_val_score(knn, x_test_transformed, y_test, cv=15)
print(training_accuracy[2])
print(test_accuracy[2])
   0.777777777777778
```