Diabetes Prediction Model

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Goal: The objective is to predict based on diagnostic measurements whether a patient has diabetes.

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.

Dependencies:

> Pregnancies: Number of times pregnant

> Glucose: Plasma glucose concentration a 2 hours in an oral 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 (years)

> Outcome: Class variable (0 or 1)

Importing Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings('ignore')
```

Loading Datasets and Visualise

```
#Importing Dataset
dataset = pd.read_csv('diabetes.csv')
```

```
#Visualising top 10 records
dataset.head()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
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

```
# Basic info of columnsabs
dataset.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
```

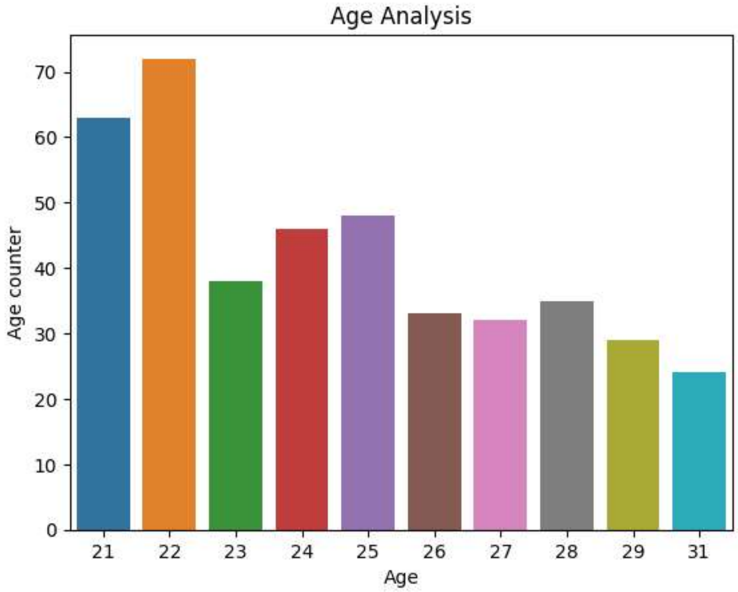
```
dataset.describe()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.348958
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

```
plt.figure(figsize=(8,8))
sns.heatmap(dataset.corr())
plt.show()
```


```
sns.barplot(x= dataset.Age.value_counts()[:10].index, y= dataset.Age.value_counts()[:10].values  )
plt.xlabel('Age')
plt.ylabel("Age counter")
plt.title("Age Analysis")
plt.show
```

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



Outcome based

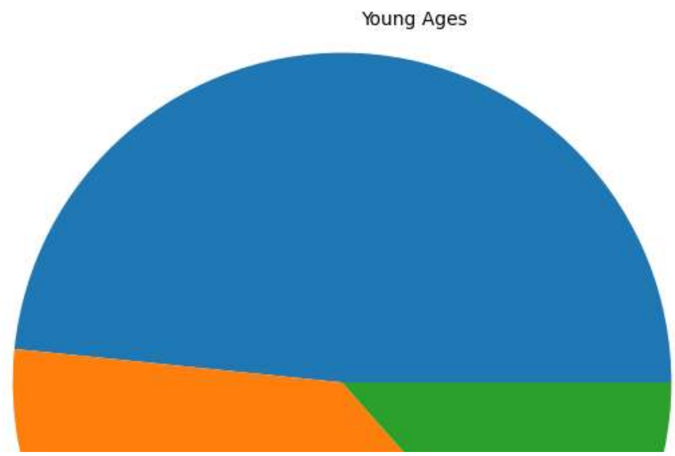
```
dataset.Outcome.value_counts()
```

```
0    500
1    268
Name: Outcome, dtype: int64
```

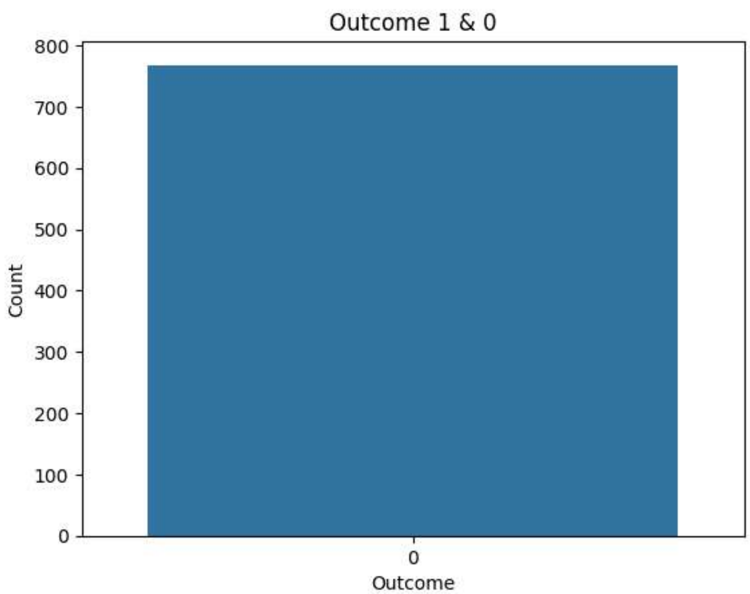
```
young_ages = dataset[(dataset.Age>=29)&(dataset.Age<40)]
middle_ages =  dataset[(dataset.Age>=40)&(dataset.Age<55)]
elderly_ages =  dataset[(dataset.Age>=55)]

print("Young Ages", len(young_ages))
print("Middle Ages", len(middle_ages))
print("Elderly Ages", len(elderly_ages))
```

```
Young Ages 194
Middle Ages 153
Elderly Ages 54
```

```
colors = ['blue','green','red']
explode= [1,1,1]
plt.figure(figsize=(8,8))
plt.pie([len(young_ages),len(middle_ages),len(elderly_ages)],labels=['Young Ages','Middle Ages','Elderly Ages'])
plt.show()
```




```
sns.countplot(dataset.Outcome)
plt.xlabel('Outcome')
plt.ylabel('Count')
plt.title('Outcome 1 & 0')
plt.show()
```




```
dataset.corr()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Ou
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.017683	-0.033523	0.544341	0.2
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357	0.221071	0.137337	0.263514	0.4
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933	0.281805	0.041265	0.239528	0.0
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.392573	0.183928	-0.113970	0.0
Insulin	-0.073535	0.331357	0.088933	0.436783	1.000000	0.197859	0.185071	-0.042163	0.1
BMI	0.017683	0.221071	0.281805	0.392573	0.197859	1.000000	0.140647	0.036242	0.2
DiabetesPedigreeFunction	-0.033523	0.137337	0.041265	0.183928	0.185071	0.140647	1.000000	0.033561	0.1
Age	0.544341	0.263514	0.239528	-0.113970	-0.042163	0.036242	0.033561	1.000000	0.2
Outcome	0.221898	0.466581	0.065068	0.074752	0.130548	0.292695	0.173844	0.238356	1.0

Data Spliting

```
Data = dataset.drop(['Outcome'],axis =1)
Outcome = dataset.Outcome.values


x_train,x_test,y_train,y_test = train_test_split(Data,Outcome, test_size=0.2, random_state=1)
```

Model Building

```
# Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
regressor = LogisticRegression()
regressor.fit(x_train,y_train)
print('Test Accuracy {:.2f}%'.format(regressor.score(x_test, y_test)*100))
```

```
Test Accuracy 77.92%
```

```
# KNN Model


from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(x_train,y_train)
print('KNN Accuracy {:.2f}%'.format(knn.score(x_test,y_test)*100))
```

```
KNN Accuracy 74.03%
```

```
# Support Vactor
from sklearn.svm import SVC
svm = SVC(random_state=1)
svm1 = SVC(kernel='linear',gamma='scale',random_state=0)
svm2 = SVC(kernel='rbf',gamma='scale',random_state=0)
svm3 = SVC(kernel='poly',gamma='scale',random_state=0)
svm4 = SVC(kernel='sigmoid',gamma='scale',random_state=0)

svm.fit(x_train,y_train)
svm1.fit(x_train,y_train)
svm2.fit(x_train,y_train)
svm3.fit(x_train,y_train)
svm4.fit(x_train,y_train)

print('SVC Accuracy : {:,.2f}%'.format(svm.score(x_test,y_test)*100))

print('SVC Liner Accuracy : {:,.2f}%'.format(svm1.score(x_test,y_test)*100))

print('SVC RBF Accuracy : {:,.2f}%'.format(svm2.score(x_test,y_test)*100))

print('SVC Ploy Accuracy : {:,.2f}%'.format(svm3.score(x_test,y_test)*100))

print('SVC Sigmoid Accuracy : {:,.2f}%'.format(svm4.score(x_test,y_test)*100))
```

```
SVC Accuracy : 78.57%
SVC Liner Accuracy : 77.92%
SVC RBF Accuracy : 78.57%
SVC Ploy Accuracy : 77.92%
SVC Sigmoid Accuracy : 50.65%
```

```
# Naive Bayes
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb.fit(x_train,y_train)
print("Naive Bayes Accuracy : {:,.2f}%".format(nb.score(x_test,y_test)*100))
```

```
Naive Bayes Accuracy : 77.27%
```

```
# Random Forest Classifier

from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators=1000, max_depth=100,random_state=1)
rf.fit(x_train,y_train)
print("Random Forest Accuracy : {:,.2f}%".format(rf.score(x_test,y_test)*100))
```

```
Random Forest Accuracy : 80.52%
```

```
# Decision Tree
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier(criterion='entropy',max_depth=4, random_state=0)
dt.fit(x_train,y_train)
print("Decision Tree Accuracy : {:,.2f}%".format(dt.score(x_test,y_test)*100))
```

```
Decision Tree Accuracy : 79.22%
```

```
# XGboost
import xgboost
xg = xgboost.XGBClassifier()
xg.fit(x_train,y_train)
print("XGboost accuracy : {:.2f}%".format(xg.score(x_test,y_test)*100))
```

```
XGboost accuracy : 75.32%
```

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