

```
In [ ]: 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
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
import warnings
warnings.filterwarnings('ignore')
```

```
In [2]: data=pd.read_csv("diabetes.csv")
```

```
In [3]: data
```

```
Out[3]:
```

	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
...
763	10	101	76	48	180	32.9	0.171	63
764	2	122	70	27	0	36.8	0.340	27
765	5	121	72	23	112	26.2	0.245	30
766	1	126	60	0	0	30.1	0.349	47
767	1	93	70	31	0	30.4	0.315	23

768 rows × 9 columns



```
In [4]: data.head()
```

```
Out[4]:
```

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



```
In [6]: data.shape
```

```
Out[6]: (768, 9)
```

In [8]: 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   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
```

In [11]: data.describe()

Out[11]:

	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	33.240659	33.780160	1.011614
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	33.998132	11.951161	0.105472
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	26.665000	29.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	32.000000	33.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	35.975000	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	67.100000	67.000000	1.000000

In [13]: data.isnull().sum() *#checking if data having null values*

```
Out[13]: Pregnancies            0
Glucose                0
BloodPressure          0
SkinThickness          0
Insulin                0
BMI                    0
DiabetesPedigreeFunction 0
Age                   0
Outcome                0
dtype: int64
```

In [18]: data.duplicated().sum()

Out[18]: 0

```
In [21]: num_duplicates=data.duplicated().sum()
```

```
In [23]: if num_duplicates>0:
          print("the data contains duplicate values ")
          data=data.drop_duplicates
          print("number of duplicate values after dropping",num_duplicates)
        else:
          print("the data dosnot contains any duplicates")
```

the data dosnot contains any duplicates

```
In [24]: data
```

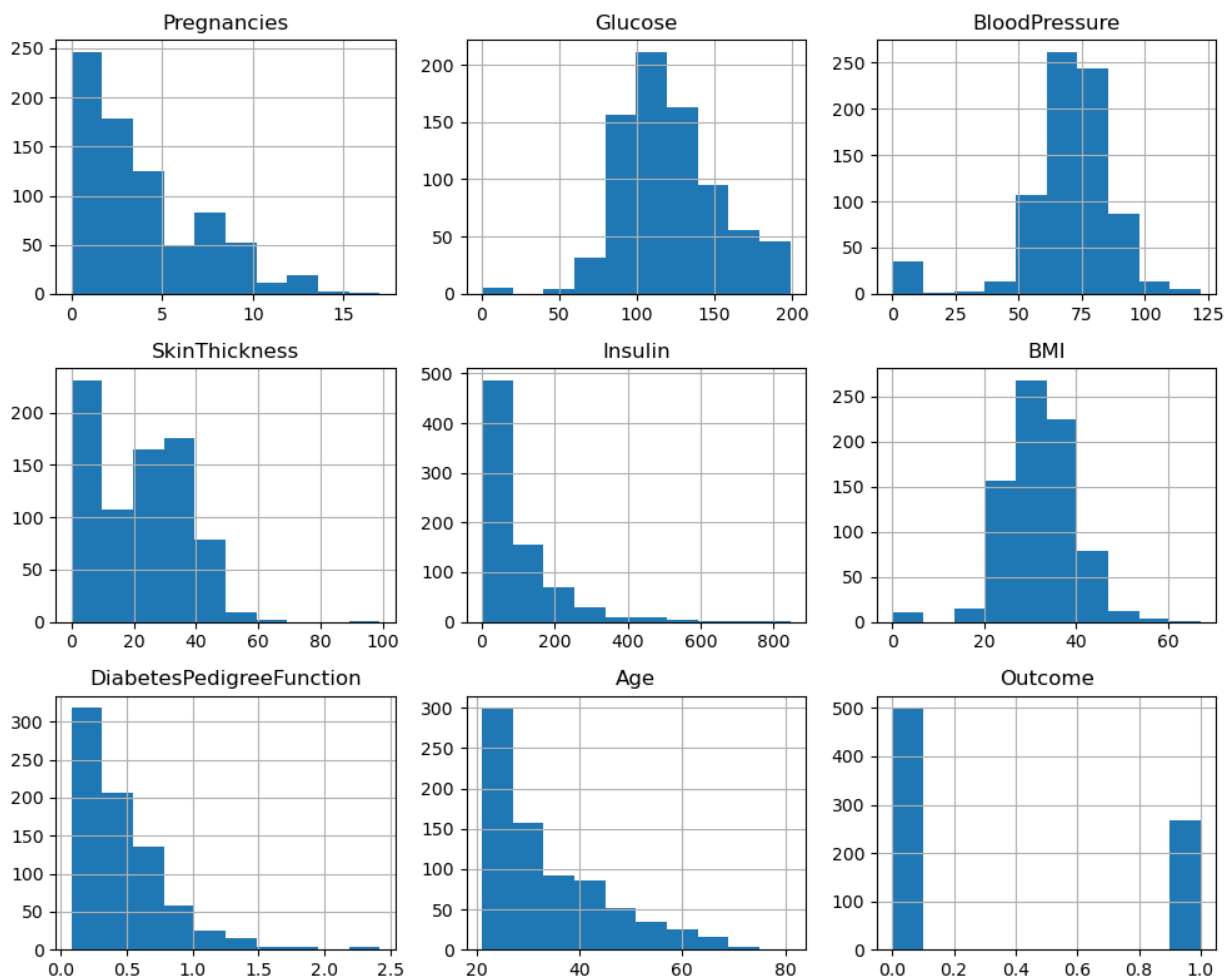
Out[24]:

	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
...
763	10	101	76	48	180	32.9	0.171	63
764	2	122	70	27	0	36.8	0.340	27
765	5	121	72	23	112	26.2	0.245	30
766	1	126	60	0	0	30.1	0.349	47
767	1	93	70	31	0	30.4	0.315	23

768 rows × 9 columns



```
In [31]: data.hist(figsize=(10,8))
plt.tight_layout()
plt.show()
```



```
In [32]: X=data.iloc[:, :-1]
X.head(5)
```

Out[32]:

	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

```
In [34]: Y=data.iloc[:,-1]
Y.head(5)
```

```
Out[34]: 0    1
         1    0
         2    1
         3    0
         4    1
         Name: Outcome, dtype: int64
```

```
In [35]: X_train, X_test, Y_train, Y_test=train_test_split(X,Y, test_size=0.30, random_state=5)
```

```
In [37]: print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
```

```
(537, 8)
(231, 8)
(537,)
(231,)
```

Train the model

```
In [38]: logistic=LogisticRegression()
logistic.fit(X_train,Y_train)
```

```
Out[38]: LogisticRegression()
```

Evaluate the Model

```
In [39]: Y_predict=logistic.predict(X_test)
print("Y_predict\n",Y_predict)
```

```
Y_predict
[0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 1 0 0 1 0 0 0 0 1 1 0 1 0 1 0 0 1 0 0 0
 0 0 0 0 0 0 1 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 1 0 0 1
 0 1 0 1 1 0 0 0 1 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 1 0 1 0 0
 1 0 0 0 1 1 1 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 1 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0 0
 0 0 0 1 1 0 0 0 0 0 0 0 0 0 1 0 1 1 0 1 0 1 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
 1 1 0 0 1 0 0 0 1 0 0 0 0 0 0 0 1 1 0 0 1 0 0 0 0 0 1 0 1 1 0 0 1 0 0 1 1 1 0
 0 0 0 0 1 0 1 0 0]
```

```
In [40]: print("Y_test\n",Y_test)
```

```
Y_test
737    0
505    0
296    1
711    0
329    0
..
405    0
315    0
131    1
364    0
322    1
Name: Outcome, Length: 231, dtype: int64
```

```
In [43]: score=accuracy_score(Y_test,Y_predict)
print("Accuracy_score:" ,score*100)
```

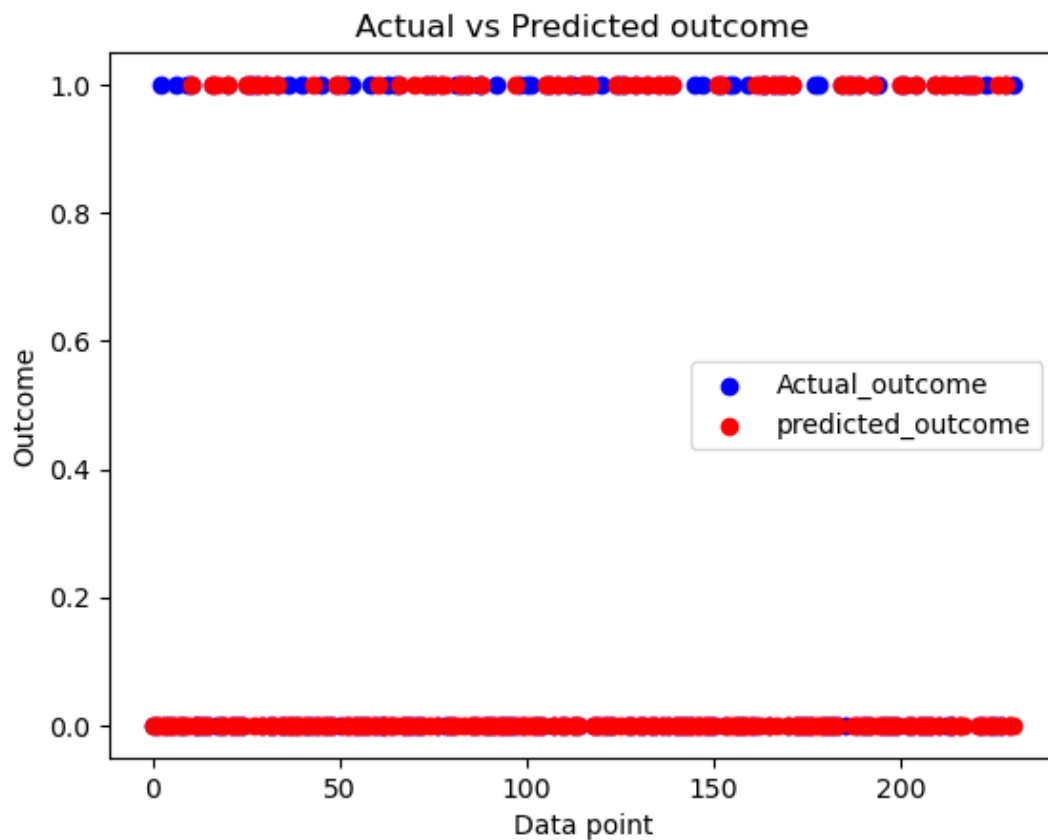
```
Accuracy_score: 79.22077922077922
```

```
In [48]: import numpy as np
```

Visually understand the performance of the model

```
In [58]: fig, ax=plt.subplots()
ax.scatter(range(len(Y_test)),Y_test, color="blue", label="Actual_outcome")
ax.scatter(range(len(Y_predict)), Y_predict, color="red", label="predicted_outcome")
ax.set_xlabel("Data point")
ax.set_ylabel("Outcome")
ax.set_title("Actual vs Predicted outcome")

ax.legend()
plt.show()
```



Use the model

once the model is trained and evaluated you can use to predict unseen dataset.