

Import libraries

In []:

```
import numpy as np
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report
```

In []:

```
from google.colab import files
uploaded = files.upload()
```

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Saving diabetes.csv to diabetes (4).csv

In []:

```
diabetes = pd.read_csv('diabetes.csv')
print(diabetes)
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	\
0	6	148	72	35	0	33.6	
1	1	85	66	29	0	26.6	
2	8	183	64	0	0	23.3	
3	1	89	66	23	94	28.1	
4	0	137	40	35	168	43.1	
..	
763	10	101	76	48	180	32.9	
764	2	122	70	27	0	36.8	
765	5	121	72	23	112	26.2	
766	1	126	60	0	0	30.1	
767	1	93	70	31	0	30.4	

	DiabetesPedigreeFunction	Age	Outcome
0	0.627	50	1
1	0.351	31	0
2	0.672	32	1
3	0.167	21	0
4	2.288	33	1
..
763	0.171	63	0
764	0.340	27	0
765	0.245	30	0
766	0.349	47	1
767	0.315	23	0

[768 rows x 9 columns]

key variables of the data set

In []:

```
print("Keys of Diabets_dataset: \n{}".format(diabetes.keys()))
Keys of Diabets_dataset:
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

Cleaning Empty Cells

In []:

```
new_diabetes = diabetes.dropna()
```

Plot each Variables

In []:

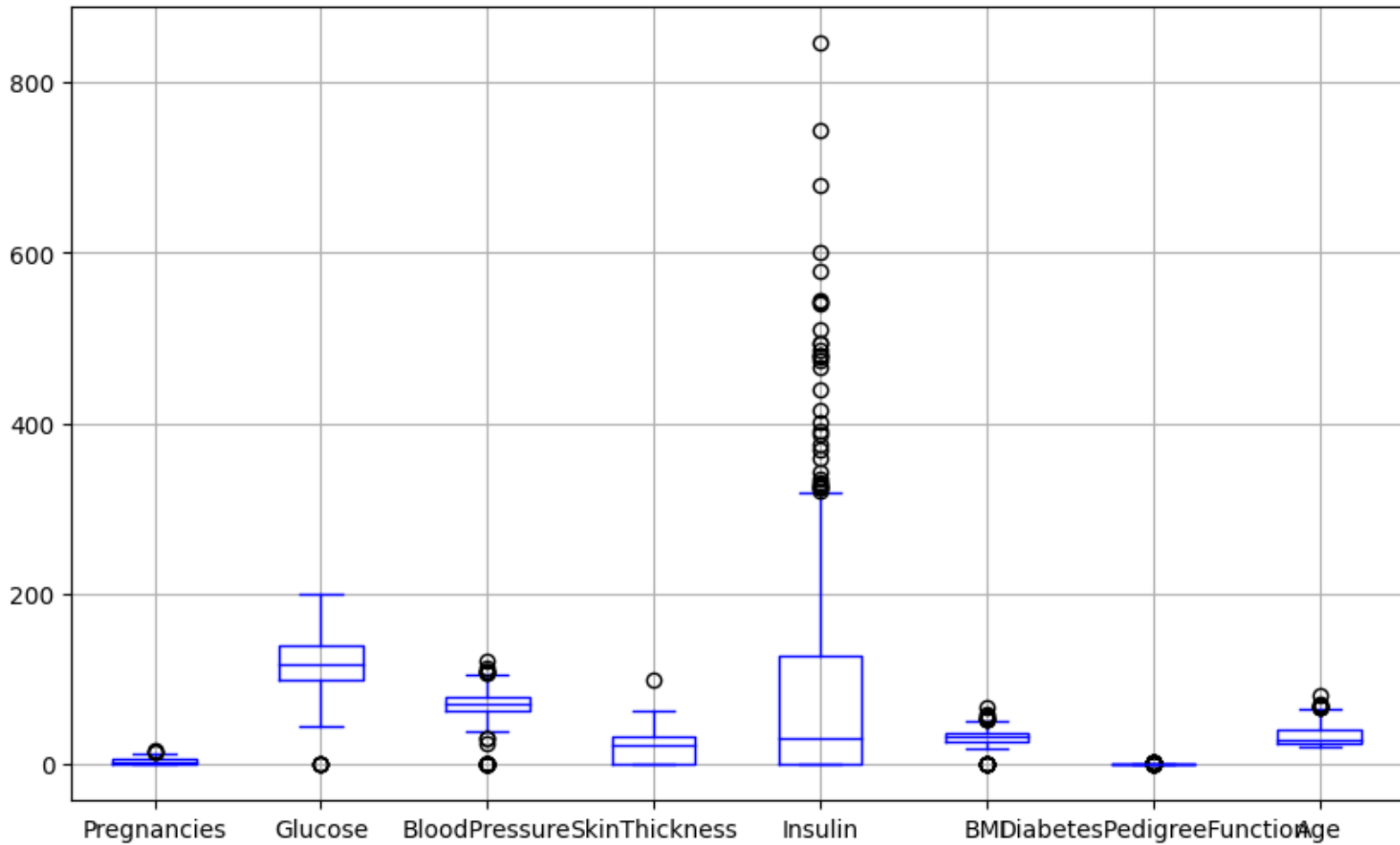
```
import seaborn as sns
import matplotlib.pyplot as plt
```

In []:

```
new_diabetes.boxplot(column=['Pregnancies', 'Glucose', 'BloodPressure',
                             'SkinThickness', 'Insulin', 'BMI', 'DiabetesPedigreeFunction',
                             'Age'], color='blue', figsize=(10, 6))
```

Out[]:

```
<Axes: >
```



Remove Outliers

In []:

```
from scipy import stats
new = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
       'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age']
z_scores = np.abs(stats.zscore(new_diabetes[new]))
threshold = 3
outliers = (z_scores > threshold).any(axis=1)

data_cleaned = new_diabetes[~outliers]
```

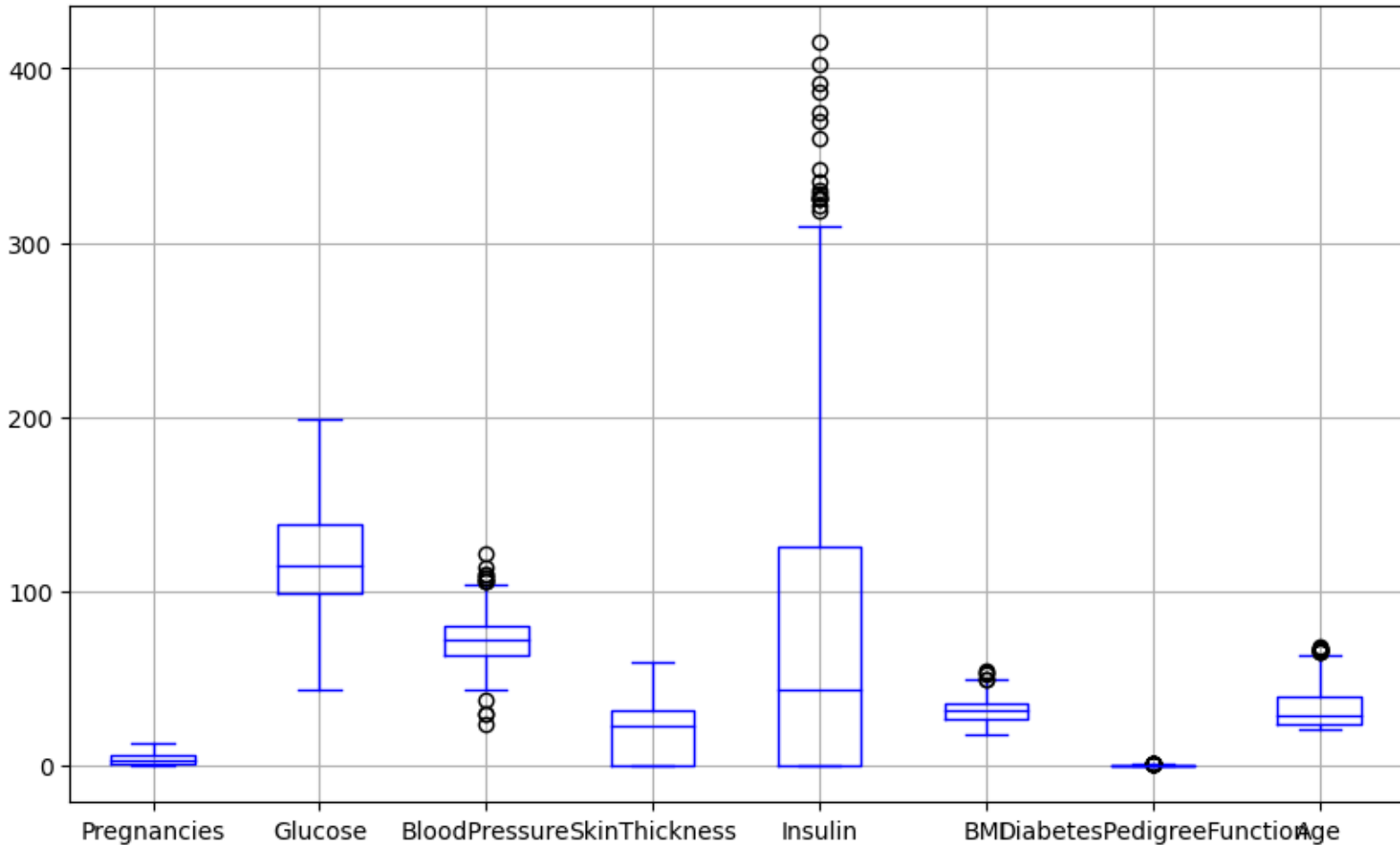
Plot Variables After removing Outliers

In []:

```
data_cleaned.boxplot(column=['Pregnancies', 'Glucose', 'BloodPressure',
                              'SkinThickness', 'Insulin', 'BMI', 'DiabetesPedigreeFunction',
                              'Age'],color='blue', figsize=(10, 6))
```

Out[]:

<Axes: >



When comparing above two boxplot charts, We can conclude that several variable's outliers have been decreased.

In []:

```
print(data_cleaned.info())
<class 'pandas.core.frame.DataFrame'>
Int64Index: 688 entries, 0 to 767
Data columns (total 9 columns):
#   Column              Non-Null Count  Dtype
---  -
0   Pregnancies         688 non-null    int64
1   Glucose             688 non-null    int64
```

```

2   BloodPressure          688 non-null    int64
3   SkinThickness          688 non-null    int64
4   Insulin                688 non-null    int64
5   BMI                    688 non-null    float64
6   DiabetesPedigreeFunction 688 non-null    float64
7   Age                    688 non-null    int64
8   Outcome                688 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 53.8 KB
None

```

I have removed the outliers above, and this summary shows there are no any null values after removing outliers. and also, before removing outliers data set has 768 rows and after removing outliers that has reduced to 688 rows.

Check Significance of dependent variables

In []:

```

# Define features (X) and binary target variable (y)

X = data_cleaned[new] # Replace with your independent variables
y = data_cleaned['Outcome'] # Replace with your binary dependent variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

#Build and train the Logistic Regression model
model = LogisticRegression()
model.fit(X_train, y_train)
print(model)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
confusion = confusion_matrix(y_test, y_pred)
classification = classification_report(y_test, y_pred)

print (model)
print(f"Accuracy: {accuracy}")
print("Confusion Matrix:\n", confusion)
print("Classification Report:\n", classification)
LogisticRegression()

```

```
LogisticRegression()
```

```
Accuracy: 0.7608695652173914
```

```
Confusion Matrix:
```

```
[[80  5]
```

```
[28 25]]
```

```
Classification Report:
```

	precision	recall	f1-score	support
0	0.74	0.94	0.83	85
1	0.83	0.47	0.60	53
accuracy			0.76	138
macro avg	0.79	0.71	0.72	138
weighted avg	0.78	0.76	0.74	138

```
/usr/local/lib/python3.10/dist-
```

```
packages/sklearn/linear_model/_logistic.py:458: 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
```

```
Please also refer to the documentation for alternative solver options:
```

```
https://scikit-learn.org/stable/modules/linear\_model.html#logistic-  
regression
```

```
n_iter_i = _check_optimize_result(
```

In [128]:

```
import statsmodels.api as sm
```

```
#Fit a logistic regression model using statsmodels
```

```
X = sm.add_constant(X)
```

```
model = sm.Logit(y, X)
```

```
result = model.fit()
```

```
p_values = result.pvalues
```

```
print(p_values)
```

```
#Get the model summary, including p-values
```

```
summary = result.summary()
```

```
print(summary)
```

```
Optimization terminated successfully.
```

```
Current function value: 0.456687
```

```
Iterations 6
```

```
const 3.105277e-34
```

```

Pregnancies          9.011362e-06
Glucose              1.139108e-22
BMI                 1.111667e-08
DiabetesPedigreeFunction 1.885311e-05
dtype: float64

```

Logit Regression Results

```

=====
=
Dep. Variable:          Outcome   No. Observations:
688
Model:                Logit      Df Residuals:
683
Method:               MLE        Df Model:
4
Date:                Fri, 13 Oct 2023   Pseudo R-squ.:
0.2798
Time:                16:56:57   Log-Likelihood:      -
314.20
converged:           True       LL-Null:      -
436.29
Covariance Type:     nonrobust   LLR p-value:      1.172e-
51
=====
=====
                                coef      std err          z      P>|z|
[0.025      0.975]
-----
const                -9.5412      0.782    -12.200      0.000      -
11.074      -8.008
Pregnancies           0.1329      0.030      4.440      0.000
0.074      0.192
Glucose               0.0368      0.004      9.799      0.000
0.029      0.044
BMI                  0.0919      0.016      5.713      0.000
0.060      0.123
DiabetesPedigreeFunction 1.4874      0.348      4.278      0.000
0.806      2.169
=====
=====

```

Get the variables below the P value

```
alpha = 0.05
```

In [129]:

```

# Identify non-significant variables
non_sig = p_values[p_values > alpha].index

# Remove non-significant variables from the feature matrix
X = X.drop(non_sig, axis=1)
Y = data_cleaned.Outcome

# Fit the model again with the selected variables
model = sm.Logit(Y, X)
result = model.fit()

summary = result.summary()
print(summary)
Optimization terminated successfully.
    Current function value: 0.456687
    Iterations 6

```

Logit Regression Results

```

=====
=
Dep. Variable:          Outcome    No. Observations:
688
Model:                Logit      Df Residuals:
683
Method:                MLE       Df Model:
4
Date:                Fri, 13 Oct 2023    Pseudo R-squ.:
0.2798
Time:                16:57:02    Log-Likelihood:    -
314.20
converged:            True      LL-Null:    -
436.29
Covariance Type:      nonrobust    LLR p-value:    1.172e-
51
=====
=====

```

		coef	std err	z	P> z	
[0.025	0.975]					

const		-9.5412	0.782	-12.200	0.000	-
11.074	-8.008					
Pregnancies		0.1329	0.030	4.440	0.000	
0.074	0.192					

Glucose		0.0368	0.004	9.799	0.000
0.029	0.044				
BMI		0.0919	0.016	5.713	0.000
0.060	0.123				
DiabetesPedigreeFunction		1.4874	0.348	4.278	0.000
0.806	2.169				
=====					
=====					

Considering the above summary, we can identify P values for each variables. According to the P values for each variables, we can get a conclusion about what are the most significance factors for affecting to the diabetes. To do that, we consider the P values of variables that are lower than the 0.05 ($P < 0.05$) That variables are,

1. Pregnancies
2. Glucose
3. BMI
4. DiabetesPedigreeFunction

Logistic regression as a binary classifier

In [130]:

```
significance_var = ['Pregnancies',
'Glucose', 'BMI', 'DiabetesPedigreeFunction']
# Define features (X) and binary target variable (y)
X = data_cleaned[significance_var] # Replace with your independent variables
Y = data_cleaned['Outcome'] # Replace with your binary dependent variable

# Split the data into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,
random_state=42)

# Build and train the Logistic Regression model
model = LogisticRegression()
model.fit(X_train, Y_train)
print(model)

# Make predictions
Y_pred = model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(Y_test, Y_pred)
confusion = confusion_matrix(Y_test, Y_pred)
classification = classification_report(Y_test, Y_pred)
```

```

print (model)
print(f"Accuracy: {accuracy}")
print("Confusion Matrix:\n", confusion)
print("Classification Report:\n", classification)
LogisticRegression()
LogisticRegression()
Accuracy: 0.782608695652174
Confusion Matrix:
[[82  3]
 [27 26]]
Classification Report:

```

	precision	recall	f1-score	support
0	0.75	0.96	0.85	85
1	0.90	0.49	0.63	53
accuracy			0.78	138
macro avg	0.82	0.73	0.74	138
weighted avg	0.81	0.78	0.76	138

Evaluating the dataset with OVR Model

In [131]:

```

#Evaluating the dataset with OVR Model
#X = data_cleaned[significance_var] # Replace with your independent
variables
#y = data_cleaned['Outcome'] # Replace with your binary dependent variable
# Create one-vs-rest logistic regression object
logreg = LogisticRegression(multi_class="ovr")

# Train model
model = logreg.fit(X_train, Y_train)

print("Test set predictions: {}".format(model.predict(X_test)))
# We calculate the predictions for y_test.

print("Test set accuracy: {:.2f}".format(logreg.score(X_test, Y_test)))
# To evaluate how well our model generalizes, we call the score method with
the test data together
# with the test labels.
Test set predictions: [0 0 0 0 1 1 0 0 0 0 0 0 1 0 1 0 0 0 0 0 1 0 1 0 0 0 1
0 0 1 0 0 1 0 0 0 0
0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 1 0 0
1 0 0 0 0 1 0 0 1 0 0 1 0 0 1 0 0 0 0 1 0 1 1 0 0 0 0 0 0 0 1 0 0 0 0 1

```

```
0 0 0 1 0 1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 1 0]
Test set accuracy: 0.78
```

Evaluating the dataset with multinomial Model

In [132]:

```
# Create multinomial logistic regression object

logreg = LogisticRegression(random_state=0, multi_class="multinomial")

# Train model
model = logreg.fit(X_train, Y_train)

print("Test set predictions: {}".format(model.predict(X_test)))
# We calculate the predictions for y_test.

print("Test set accuracy: {:.2f}".format(logreg.score(X_test, Y_test)))
# To evaluate how well our model generalizes, we call the score method with
the test data together
# with the test labels.
Test set predictions: [0 0 0 0 1 1 0 0 0 0 0 0 1 0 1 0 0 0 0 0 1 0 1 0 0 0 1
0 0 1 0 0 1 0 0 0 0
0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0
1 0 0 0 0 1 0 0 1 0 0 1 0 0 1 0 0 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1
0 0 0 1 0 1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 1 0]
Test set accuracy: 0.78
```

When considering the accuracy results for the above several logistic regression model, that all models results are the same. (0.78) therefore, according to the our diabetes data set, we can get any suitable best fitted logistic regression model for the to predict whether or not a patient has diabetes.