This Machine Learning model will detect if a person have diabetes or not

Objective :

In this we have to make a machine learning model that is capable to identify between those people that have diabetes and those who do not have diabetes.

Models used for testing :

In this stage we are applying SVM , Logistic Regression, Polynomial Regression, Linear Regression models to test which model gives us best accuracy score with least number of miss classified samples from the diabetes data Frame.

Importing the required python libraries

In [221]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt #importing pyplot
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, recall_score, precision_score
from sklearn.preprocessing import MinMaxScaler
import seaborn as sb

from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC
```

In [222]:
```python
### read csv file
df = pd.read_csv('diabetes.csv')
```

In [223]:
```python
df
```

Out[223]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

768 rows × 9 columns

In [224]:
```python
df.shape #checking the shape of the dataframe
```

Out[224]:
```
(768, 9)
```

In [225]:
```python
# gives information of the data types
df.info
```

Out[225]:
```
<bound method DataFrame.info of      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]>
```

In [226]:
```python
df.isnull().sum() # checking if the dataframe has any null value or not
```

Out[226]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

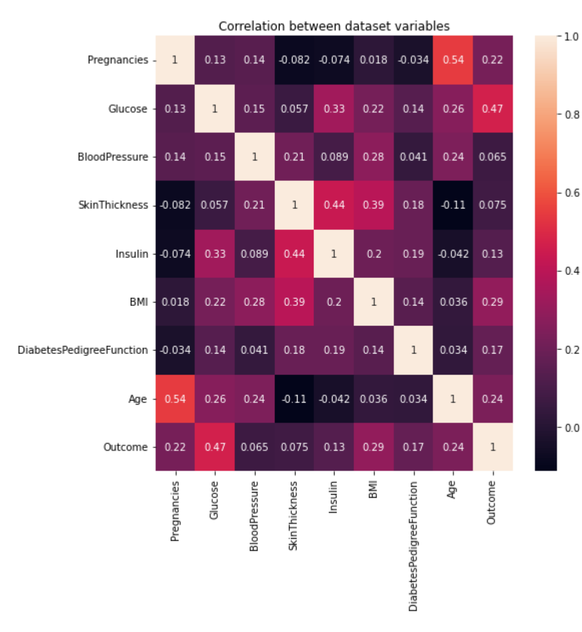
In [227]:
```python
# basic statistic details about the data (note only numerical columns would be displayed here unless param
eter
# include="all")
df.describe()
```

Out[227]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcom
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.00000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.34895
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.47695
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.00000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.00000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.00000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.00000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.00000

In [228]:
```python
 #print a graph for correlation
plt.figure(figsize=(8,8))
plt.title('Correlation between dataset variables')
sb.heatmap(df.corr(), annot=True)
```

Out[228]:
```
<AxesSubplot:title={'center':'Correlation between dataset variables'}>
```



In [229]:
```python
df.Outcome.value_counts() # getting the number of classes in the target columns
```

Out[229]:
```
0    500
1    268
Name: Outcome, dtype: int64
```

In [230]:
```python
x = df.iloc[:,:-1] # features
```

In [231]:
```python
y = df.iloc[:,8] #target values
```

In [232]:
```python
np.bincount(y)
```

Out[232]:
```
array([500, 268])
```

Applying SVM on the dibetes dataFrame

In [233]:
```python
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=.2,random_state=12)
```

In [234]:
```python
p = [{'kernel':['linear'],'C':[.01,1,10]},{'kernel':['rbf'],'gamma':[.001,.01,.1,10]}]
clf = GridSearchCV(SVC(),param_grid=p,cv=5,scoring='accuracy')
clf.fit(xtrain,ytrain)
```

Out[234]:
```
GridSearchCV(cv=5, estimator=SVC(),
             param_grid=[{'C': [0.01, 1, 10], 'kernel': ['linear']},
                         {'gamma': [0.001, 0.01, 0.1, 10], 'kernel': ['rbf']}],
             scoring='accuracy')
```

In [235]:
```python
clf.best_score_ #getting the best model with the highest score
```

Out[235]:
```
0.7654671464747435
```

In [236]:
```python
clf.best_params_ # getting the best model with the best hyper parameters with the highest score
```

Out[236]:
```
{'C': 10, 'kernel': 'linear'}
```

In [237]:
```python
clf1 = clf.best_estimator_ # saving the model with the best hyper parameter in the clf variable
clf1
```

Out[237]:
```
SVC(C=10, kernel='linear')
```

In [238]:
```python
pred = clf1.predict(xtest)
```

In [239]:
```python
from sklearn.metrics import accuracy_score
accuracy_score(ytest,pred)
```

Out[239]:
```
0.8116883116883117
```

Plotting confusion matrix

In [240]:
```python
c1 = confusion_matrix(ytest,pred)
c1
```

Out[240]:
```
array([[90,  9],
       [20, 35]])
```

In [241]:
```python
np.bincount(ytest) # it returns the number of samples in each class
```

Out[241]:
```
array([99, 55])
```

In [242]:
```python
recall_score(ytest,pred)
```

Out[242]:
```
0.6363636363636364
```

In [243]:
```python
precision_score(ytest,pred)
```

Out[243]:
```
0.7954545454545454
```

now testing the model

In [244]:
```python
pred_train = clf1.predict(xtrain)
```

In [245]:
```python
np.where(pred_train!=ytrain) #getting all the missclassified samples in train dataset
```

Out[245]:
```
(array([  4,   5,   6,  11,  12,  19,  27,  30,  31,  37,  41,  43,  46,
         50,  56,  57,  64,  75,  83,  92,  93, 101, 103, 111, 116, 118,
        121, 125, 134, 137, 143, 153, 154, 159, 168, 174, 175, 179, 188,
        192, 193, 195, 196, 197, 198, 200, 202, 204, 208, 211, 231, 235,
        236, 238, 239, 246, 248, 252, 254, 260, 263, 267, 269, 272, 274,
        283, 284, 289, 301, 302, 305, 306, 320, 331, 333, 339, 340, 345,
        348, 352, 357, 358, 361, 362, 372, 373, 380, 386, 388, 389, 400,
        404, 406, 408, 413, 422, 429, 431, 441, 445, 455, 457, 458, 459,
        465, 472, 474, 478, 481, 482, 485, 488, 491, 492, 494, 496, 498,
        500, 502, 504, 506, 508, 510, 518, 522, 523, 529, 534, 546, 551,
        556, 557, 565, 568, 569, 571, 572, 575, 579, 582, 587, 589, 591,
        600, 609, 613]),)
```

In [246]:
```python
pred_test = clf1.predict(xtest)
pred_test
```

Out[246]:
```
array([0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1,
       0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0,
       1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0])
```

In [247]:
```python
np.where(pred_test!=ytest) #getting all the missclassified samples in test dataset
```

Out[247]:
```
(array([  6,   7,  17,  18,  20,  26,  27,  56,  57,  64,  79,  82,  83,
         86, 100, 104, 106, 107, 121, 123, 126, 129, 130, 131, 135, 136,
        138, 147, 152]),)
```

Conclusion SVm model have the accuracy score of 81%

Now Applying Logistic Regression on Dibetes Dataframe

In [248]:
```python
x # x has all the features
```

Out[248]:

	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 × 8 columns

In [249]:
```python
y # y has all the values of the target columns
```

Out[249]:
```
0      1
1      0
2      1
3      0
4      1
      ..
763    0
764    0
765    0
766    1
767    0
Name: Outcome, Length: 768, dtype: int64
```

Splitting data into train and test dataset

In [250]:
```python
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=.2,random_state=12)
```

In [251]:
```python
xtrain.shape
```

Out[251]:
```
(614, 8)
```

In [252]:
```python
xtest.shape
```

Out[252]:
```
(154, 8)
```

In [253]:
```python
ytrain.shape
```

Out[253]:
```
(614,)
```

In [254]:
```python
ytest.shape
```

Out[254]:
```
(154,)
```

Transforming data using Feature Scaling (MinMaxScaler) OR Normalizing data using MinMax Scalar. It is very important to normalize data in the dataframe before feeding it to Logistic regression

In [255]:
```python
from sklearn.preprocessing import MinMaxScaler
minmax_scaler = MinMaxScaler() # initialization of minmaxScalar
```

In [256]:
```python
minmax_scaler_train = minmax_scaler.fit_transform(xtrain)
minmax_scaler_test = minmax_scaler.transform(xtest)
```

Use PCA ->It reduces dimension or Features with the minimum loss of information to reduce model training time and remove less important features in the dataset

In [257]:
```python
from sklearn.decomposition import PCA
pca = PCA(n_components=.95)
```

In [258]:
```python
pca_train = pca.fit_transform(minmax_scaler_train)
pca_test = pca.transform(minmax_scaler_test)
```

In [259]:
```python
pca_train.shape
```

Out[259]:
```
(614, 7)
```

In [260]:
```python
pca_test.shape
```

Out[260]:
```
(154, 7)
```

Now applying Logistic Regression

In [261]:
```python
from sklearn.linear_model import LogisticRegression
log = LogisticRegression(multi_class='multinomial',max_iter=10000)
```

In [262]:
```python
log.fit(pca_train,ytrain)
```

Out[262]:
```
LogisticRegression(max_iter=10000, multi_class='multinomial')
```

In [263]:
```python
pred = log.predict(pca_test)
pred
```

Out[263]:
```
array([0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1,
       0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0])
```

In [264]:
```python
ytest
```

Out[264]:
```
229    0
235    1
750    1
365    0
449    0
      ..
154    1
69     0
561    1
37     1
538    0
Name: Outcome, Length: 154, dtype: int64
```

In [265]:
```python
score = log.score(pca_test,ytest)
score
```

Out[265]:
```
0.8051948051948052
```

Conclusion Logistic regression with PCA and minMaxScalar transformation gives accuracy score of 80%

Now what if we remove PCA and use Logistic regression directply after normalizing data using MinMax scalar

In [266]:
```python
log.fit(minmax_scaler_train,ytrain)
```

Out[266]:
```
LogisticRegression(max_iter=10000, multi_class='multinomial')
```

In [267]:
```python
pred = log.predict(minmax_scaler_test)
pred
```

Out[267]:
```
array([0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1,
       0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0])
```

In [268]:
```python
score = log.score(minmax_scaler_test,ytest)
score
```

Out[268]:
```
0.8116883116883117
```

So if we do not use PCA the accuracy score goes from 80 -> 81%

What if we use standar scalar instead of minMax Scalar

In [269]:
```python
from sklearn.preprocessing import StandardScaler
std = StandardScaler()
```

In [270]:
```python
std_train = std.fit_transform(xtrain)
std_test = std.transform(xtest)
```

In [271]:
```python
log.fit(std_train,ytrain)
```

Out[271]:
```
LogisticRegression(max_iter=10000, multi_class='multinomial')
```

In [272]:
```python
pred = log.predict(std_test)
```

In [273]:
```python
score = log.score(std_test,ytest)
score
```

Out[273]:
```
0.8116883116883117
```

There is no change in the Logistic regression score even if we use standard scalar

what if we use Logistic regression directly without any normalization

In [274]:
```python
log.fit(xtrain,ytrain)
```

Out[274]:
```
LogisticRegression(max_iter=10000, multi_class='multinomial')
```

In [275]:
```python
pred = log.predict(xtest)
```

In [276]:
```python
score = log.score(xtest,ytest)
```

In [277]:
```python
score
```

Out[277]:
```
0.8181818181818182
```

Still no improvement in the model accuracy even if we use Logistic regression directly

Now Applying Polynomial Regression on Dibetes Dataset

In [278]:
```python
# SimpleRegression => Simple Linear regression and multi Linear regression
# If r2_score is not close to 1 then Linear regression is not good for the the dataset
# Here now we have to use different Regression Model (Polynomial Regression)

# Polynomial Regression = Polynomial Features + Linear Regression
#It's function is to transform data
```

In [279]:
```python
from sklearn.preprocessing import PolynomialFeatures
poly = PolynomialFeatures(degree=2)
poly_x_train = poly.fit_transform(xtrain) # Tranforming x (input data) OR here in this case train_input
```

In [280]:
```python
poly_x_train.shape
```

Out[280]:
```
(614, 45)
```

In [281]:
```python
from sklearn.linear_model import LinearRegression
lr = LinearRegression() # Initializing Linear regression
```

In [282]:
```python
lr.fit(poly_x_train,ytrain) # training the Linear regression model after polynomial transformation of data
```

Out[282]:
```
LinearRegression()
```

In [283]:
```python
from sklearn.metrics import r2_score,mean_squared_error #testing model accuracy
pred_train = lr.predict(poly_x_train) # Running Predictions on train dataset
```

In [284]:
```python
score_train = r2_score(ytrain,pred_train) # scoring our Polynomial regression model
score_train
```

Out[284]:
```
0.17397385379508412
```

In [285]:
```python
# Just like what we did with our training data we need to transform the test input
poly_x_test = poly.transform(xtest)
```

In [286]:
```python
pred_test = lr.predict(poly_x_test) #Running prediction on test dataset
score_test = r2_score(ytest,pred_test)
score_test
```

Out[286]:
```
0.010692342823729883
```

So here we can see that polynomial transformation of data before applying Linear Regression did not give us a model with a good score that means here Polynomial Transformation of data will not work

Now applying Raw Linear Regression model on diebetes dataset

In [287]:
```python
lr.fit(xtrain,ytrain)
```

Out[287]:
```
LinearRegression()
```

In [288]:
```python
predict_test = lr.predict(xtest)
```

In [289]:
```python
score_test = r2_score(ytest,predict_test)
score_test
```

Out[289]:
```
0.28600493783377956
```

In [290]:
```python
predict_train = lr.predict(xtrain)
```

In [291]:
```python
score_train = r2_score(ytrain,predict_train)
score_train
```

Out[291]:
```
0.303816297947065
```

Linear Regression Model is also not suitable for classifiying diebets patient in the diebetes dataset

Hence according to my analysis SVM and Logisitc Regression are the only two Machine Learning model with the descent score of 81% and can be used in the dibetes dataset.