

```
# importing the libraries
```

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.metrics import accuracy_score
```

```
#loading the PIMA diabetes dataset
```

```
diabetes_dataset = pd.read_csv('/content/diabetes.csv')
```

```
#looking at the dataset
```

```
diabetes_dataset.head()
```

```
{"summary":{"\n  \"name\": \"diabetes_dataset\",\n  \"rows\": 768,\n  \"fields\": [\n    {\n      \"column\": \"Pregnancies\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 3,\n        \"min\": 0,\n        \"max\": 17,\n        \"num_unique_values\": 17,\n        \"samples\": [\n          6,\n          1,\n          3\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      },\n      \"column\": \"Glucose\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 31,\n        \"min\": 0,\n        \"max\": 199,\n        \"num_unique_values\": 136,\n        \"samples\": [\n          151,\n          101,\n          112\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      },\n      \"column\": \"BloodPressure\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 19,\n        \"min\": 0,\n        \"max\": 122,\n        \"num_unique_values\": 47,\n        \"samples\": [\n          86,\n          46,\n          85\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      },\n      \"column\": \"SkinThickness\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 15,\n        \"min\": 0,\n        \"max\": 99,\n        \"num_unique_values\": 51,\n        \"samples\": [\n          7,\n          12,\n          48\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      },\n      \"column\": \"Insulin\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 115,\n        \"min\": 0,\n        \"max\": 846,\n        \"num_unique_values\": 186,\n        \"samples\": [\n          52,\n          41,\n          183\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      },\n      \"column\": \"BMI\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 7.8841603203754405,\n        \"min\": 0.0,\n        \"max\": 67.1,\n        \"num_unique_values\": 248,\n        \"samples\": [\n          19.9,\n          31.0,\n          38.1\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      },\n      \"column\": \"DiabetesPedigreeFunction\",\n      \"properties\": {\n        \"dtype\": \"number\",\n        \"std\": 0.471471,\n        \"min\": 0.078,\n        \"max\": 2.42,\n        \"num_unique_values\": 352,\n        \"samples\": [\n          1.0,\n          1.5,\n          2.0\n        ],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    ]\n  }\n}
```

```

{"properties": {\n      \"dtype\": \"number\", \n      \"std\": 0.33132859501277484, \n      \"min\": 0.078, \n      \"max\": 2.42, \n      \"num_unique_values\": 517, \n      \"samples\": [\n        1.731, \n        0.426, \n        0.138\n      ], \n      \"semantic_type\": \"\", \n      \"description\": \"\"\n    }, \n    {\n      \"column\": \"Age\", \n      \"properties\": {\n        \"dtype\": \"number\", \n        \"std\": 11, \n        \"min\": 21, \n        \"max\": 81, \n        \"num_unique_values\": 52, \n        \"samples\": [\n          60, \n          47, \n          72\n        ], \n        \"semantic_type\": \"\", \n        \"description\": \"\"\n      }, \n      {\n        \"column\": \"Outcome\", \n        \"properties\": {\n          \"dtype\": \"number\", \n          \"std\": 0, \n          \"min\": 0, \n          \"max\": 1, \n          \"num_unique_values\": 2, \n          \"samples\": [\n            0, \n            1\n          ], \n          \"semantic_type\": \"\", \n          \"description\": \"\"\n        }\n      }\n    ], \n    \"type\": \"dataframe\", \n    \"variable_name\": \"diabetes_dataset\"}

```

fetching number of rows and columns in our dataset

```
diabetes_dataset.shape
```

```
(768, 9)
```

```
diabetes_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
```

As we can observe, there are no missing values in the dataset and all the columns are numeric. Thus there is no issue since ml models work with numbers and not strings.

```
diabetes_dataset.describe() #statistical information
```

```

{"summary": {\n  \"name\": \"diabetes_dataset\", \n  \"rows\": 8, \n  \"fields\": [\n    {\n      \"column\": \"Pregnancies\", \n      \"properties\": {\n        \"dtype\": \"number\", \n        \"std\": 269.85223453356366, \n        \"min\": 0.0, \n        \"max\": 768.0, \n

```

```

\"num_unique_values\": 8,\n          \"samples\": [\n
3.8450520833333335,\n          3.0,\n          768.0\n          ],\n
\"semantic_type\": \"\",\n          \"description\": \"\"\n          }\n
n    },\n    {\n          \"column\": \"Glucose\",\n          \"properties\":\n
{\n          \"dtype\": \"number\",\n          \"std\":\n
243.73802348295857,\n          \"min\": 0.0,\n          \"max\": 768.0,\n
\"num_unique_values\": 8,\n          \"samples\": [\n
120.89453125,\n          117.0,\n          768.0\n          ],\n
\"semantic_type\": \"\",\n          \"description\": \"\"\n          }\n
n    },\n    {\n          \"column\": \"BloodPressure\",\n          \"properties\": {\n          \"dtype\": \"number\",\n          \"std\":\n
252.85250535810619,\n          \"min\": 0.0,\n          \"max\": 768.0,\n
\"num_unique_values\": 8,\n          \"samples\": [\n
69.10546875,\n          72.0,\n          768.0\n          ],\n
\"semantic_type\": \"\",\n          \"description\": \"\"\n          }\n
n    },\n    {\n          \"column\": \"SkinThickness\",\n          \"properties\": {\n          \"dtype\": \"number\",\n          \"std\":\n
263.7684730531098,\n          \"min\": 0.0,\n          \"max\": 768.0,\n
\"num_unique_values\": 7,\n          \"samples\": [\n          768.0,\n
20.536458333333332,\n          32.0\n          ],\n
\"semantic_type\": \"\",\n          \"description\": \"\"\n          }\n
n    },\n    {\n          \"column\": \"Insulin\",\n          \"properties\":\n
{\n          \"dtype\": \"number\",\n          \"std\":\n
350.26059167945886,\n          \"min\": 0.0,\n          \"max\": 846.0,\n
\"num_unique_values\": 7,\n          \"samples\": [\n          768.0,\n
79.79947916666667,\n          127.25\n          ],\n
\"semantic_type\": \"\",\n          \"description\": \"\"\n          }\n
n    },\n    {\n          \"column\": \"BMI\",\n          \"properties\": {\n          \"dtype\": \"number\",\n          \"std\": 262.05117817552093,\n          \"min\": 0.0,\n          \"max\": 768.0,\n          \"num_unique_values\":\n
8,\n          \"samples\": [\n          31.992578124999998,\n
32.0,\n          768.0\n          ],\n          \"semantic_type\": \"\",\n          \"description\": \"\"\n          }\n    },\n    {\n          \"column\":\n
\"DiabetesPedigreeFunction\",\n          \"properties\": {\n          \"dtype\": \"number\",\n          \"std\": 271.3005221658502,\n          \"min\": 0.078,\n          \"max\": 768.0,\n          \"num_unique_values\": 8,\n          \"samples\": [\n
0.47187630208333325,\n          0.3725,\n          768.0\n          ],\n
\"semantic_type\": \"\",\n          \"description\": \"\"\n          }\n
n    },\n    {\n          \"column\": \"Age\",\n          \"properties\": {\n          \"dtype\": \"number\",\n          \"std\": 260.1941178528413,\n          \"min\": 11.76023154067868,\n          \"max\": 768.0,\n          \"num_unique_values\": 8,\n          \"samples\": [\n
33.240885416666664,\n          29.0,\n          768.0\n          ],\n
\"semantic_type\": \"\",\n          \"description\": \"\"\n          }\n
n    },\n    {\n          \"column\": \"Outcome\",\n          \"properties\":\n
{\n          \"dtype\": \"number\",\n          \"std\":\n
271.3865920388932,\n          \"min\": 0.0,\n          \"max\": 768.0,\n
\"num_unique_values\": 5,\n          \"samples\": [\n

```

```
0.3489583333333333,\n          1.0,\n          0.4769513772427971\n],\n  \"semantic_type\": \"\",\n  \"description\": \"\"\n}\n  }\n  ],\n  \"type\": \"dataframe\"}
```

```
diabetes_dataset['Outcome'].value_counts()
```

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

This shows that 500 patients do not have diabetes while 268 patients have diabetes.

0 ---> Not diabetic, 1 ---> Diabetic

```
diabetes_dataset.groupby('Outcome').mean()
```

```
{\"summary\": \"{\\n  \"name\": \"diabetes_dataset\",\\n  \"rows\": 2,\\n  \"fields\": [\\n    {\\n      \"column\": \"Outcome\",\\n      \"properties\": {\\n        \"dtype\": \"number\",\\n        \"std\": 0,\\n        \"min\": 0,\\n        \"max\": 1,\\n        \"num_unique_values\": 2,\\n        \"samples\": [\\n          1,\\n          0\\n        ],\\n        \"semantic_type\": \"\",\\n        \"description\": \"\"\\n      }\\n    },\\n    {\\n      \"column\": \"Pregnancies\",\\n      \"properties\": {\\n        \"dtype\": \"number\",\\n        \"std\": 1.108511248584296,\\n        \"min\": 3.298,\\n        \"max\": 4.865671641791045,\\n        \"num_unique_values\": 2,\\n        \"samples\": [\\n          4.865671641791045,\\n          3.298\\n        ],\\n        \"semantic_type\": \"\",\\n        \"description\": \"\"\\n      }\\n    },\\n    {\\n      \"column\": \"Glucose\",\\n      \"properties\": {\\n        \"dtype\": \"number\",\\n        \"std\": 22.116505963980842,\\n        \"min\": 109.98,\\n        \"max\": 141.25746268656715,\\n        \"num_unique_values\": 2,\\n        \"samples\": [\\n          141.25746268656715,\\n          109.98\\n        ],\\n        \"semantic_type\": \"\",\\n        \"description\": \"\"\\n      }\\n    },\\n    {\\n      \"column\": \"BloodPressure\",\\n      \"properties\": {\\n        \"dtype\": \"number\",\\n        \"std\": 1.8672051632998017,\\n        \"min\": 68.184,\\n        \"max\": 70.82462686567165,\\n        \"num_unique_values\": 2,\\n        \"samples\": [\\n          70.82462686567165,\\n          68.184\\n        ],\\n        \"semantic_type\": \"\",\\n        \"description\": \"\"\\n      }\\n    },\\n    {\\n      \"column\": \"SkinThickness\",\\n      \"properties\": {\\n        \"dtype\": \"number\",\\n        \"std\": 1.7678935989570275,\\n        \"min\": 19.664,\\n        \"max\": 22.16417910447761,\\n        \"num_unique_values\": 2,\\n        \"samples\": [\\n          22.16417910447761,\\n          19.664\\n        ],\\n        \"semantic_type\": \"\",\\n        \"description\": \"\"\\n      }\\n    },\\n    {\\n      \"column\": \"Insulin\",\\n      \"properties\": {\\n        \"dtype\": \"number\",\\n        \"std\":
```

```
22.304849659757796,\n                \"min\": 68.792,\n                \"max\": 100.33582089552239,\n                \"num_unique_values\": 2,\n                \"samples\": [\n                    100.33582089552239,\n                    68.792\n                ],\n                \"semantic_type\": \"\", \n                \"description\": \"\"\n            },\n            {\n                \"column\": \"BMI\", \n                \"properties\": {\n                    \"dtype\": \"number\", \n                    \"std\": 3.4212211239962618,\n                    \"min\": 30.3042,\n                    \"max\": 35.14253731343284,\n                    \"num_unique_values\": 2,\n                    \"samples\": [\n                        35.14253731343284,\n                        30.3042\n                    ],\n                    \"semantic_type\": \"\", \n                    \"description\": \"\" \n                },\n                {\n                    \"column\": \"DiabetesPedigreeFunction\", \n                    \"properties\": {\n                        \"dtype\": \"number\", \n                        \"std\": 0.08539445753677459,\n                        \"min\": 0.429734,\n                        \"max\": 0.5505,\n                        \"num_unique_values\": 2,\n                        \"samples\": [\n                            0.5505,\n                            0.429734\n                        ],\n                        \"semantic_type\": \"\", \n                        \"description\": \"\" \n                    },\n                    {\n                        \"column\": \"Age\", \n                        \"properties\": {\n                            \"dtype\": \"number\", \n                            \"std\": 4.155782645191446,\n                            \"min\": 31.19,\n                            \"max\": 37.06716417910448,\n                            \"num_unique_values\": 2,\n                            \"samples\": [\n                                37.06716417910448,\n                                31.19\n                            ],\n                            \"semantic_type\": \"\", \n                            \"description\": \"\" \n                        }\n                    }\n                }\n            ],\n            \"type\": \"dataframe\"}
```

Some useful insights from this outcome could be that those people who have diabetes have high amounts of glucose and blood pressure and also as we can see that the age group which is in the range of 37 or above or to be precise age group in the range of 35 and above are susceptible to diabetes whereas the younger age groups are not.

```
# splitting the dataset into training data and testing data
X=diabetes_dataset.drop('Outcome',axis=1)
y=diabetes_dataset['Outcome']
```

```
print(X)
```

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

[768 rows x 8 columns]

```
print(y)
```

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

As we can see, the features here have different ranges. With pregnancies ranging in single digits to glucose levels ranging in hundreds and this is the same with other columns as well. Thus we need to scale all of them down to a particular range since this will help us in giving more accurate results later on. Therefore we perform standardization next

```
# Standardization
```

```
scaler = StandardScaler()
```

```
#fitting the data
```

```

scaler.fit(X)

#transforming the features data
scaled_data=scaler.transform(X)

print(scaled_data)

[[ 0.63994726  0.84832379  0.14964075 ...  0.20401277  0.46849198
  1.4259954 ]
 [-0.84488505 -1.12339636 -0.16054575 ... -0.68442195 -0.36506078
 -0.19067191]
 [ 1.23388019  1.94372388 -0.26394125 ... -1.10325546  0.60439732
 -0.10558415]
 ...
 [ 0.3429808   0.00330087  0.14964075 ... -0.73518964 -0.68519336
 -0.27575966]
 [-0.84488505  0.1597866  -0.47073225 ... -0.24020459 -0.37110101
  1.17073215]
 [-0.84488505 -0.8730192   0.04624525 ... -0.20212881 -0.47378505
 -0.87137393]]

X= scaled_data

print(X)

[[ 0.63994726  0.84832379  0.14964075 ...  0.20401277  0.46849198
  1.4259954 ]
 [-0.84488505 -1.12339636 -0.16054575 ... -0.68442195 -0.36506078
 -0.19067191]
 [ 1.23388019  1.94372388 -0.26394125 ... -1.10325546  0.60439732
 -0.10558415]
 ...
 [ 0.3429808   0.00330087  0.14964075 ... -0.73518964 -0.68519336
 -0.27575966]
 [-0.84488505  0.1597866  -0.47073225 ... -0.24020459 -0.37110101
  1.17073215]
 [-0.84488505 -0.8730192   0.04624525 ... -0.20212881 -0.47378505
 -0.87137393]]

```

Train Test Split

```

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,strat
ify=2,random_state=2)

```

Training the data

```

classifier = svm.SVC(kernel='linear',gamma='auto')

# training the svm classifier
classifier.fit(X_train,y_train)

```

```
SVC(gamma='auto', kernel='linear')
```

Model Evaluation

```
# accuracy score of the training data
X_train_prediction = classifier.predict(X_train)
training_data_accuracy = accuracy_score(X_train_prediction,y_train)
print(f'Accuracy score of the training data is:
{training_data_accuracy*100}%')

Accuracy score of the training data is:77.19869706840392%

# accuracy score of the testing data
X_test_prediction = classifier.predict(X_test)
test_data_accuracy = accuracy_score(X_test_prediction,y_test)
print(f'Accuracy score of the test data is:{test_data_accuracy*100}%')

Accuracy score of the test data is:76.62337662337663%
```

Making a Predictive System

```
# for this example..the output is 0. thus we need to test it.
input_data=(4,110,92,0,0,37.6,0.191,30)

#converting it into np array
input_data_np=np.asarray(input_data)

#reshaping it so that the model knows that we only want to know output
of one input.
input_data_resaped=np.reshape(input_data_np,(1,-1))

# standardize it
std_data=scaler.transform(input_data_resaped)
print(std_data)

#check the output
prediction=classifier.predict(std_data)
print(prediction)

if(prediction[0]==0):
    print("The patient is non-diabetic")
else:
    print("The patient is diabetic")

[[ 0.04601433 -0.34096773  1.18359575 -1.28821221 -0.69289057
  0.71168975
 -0.84827977 -0.27575966]]
[0]
The patient is non-diabetic
```



```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:493:  
UserWarning: X does not have valid feature names, but StandardScaler  
was fitted with feature names  
warnings.warn(
```