DECISION TREE - DIABETES PREDICTION

July 26, 2022

#

DIABETES PREDICTION

0.0.1 Table of Contents

0.0.2 1. PROJECT INTRODUCTION

Diabetes is a chronic disease that occurs either when the pancreas fails to produce enough insulin or when one's body is unable to effectively utilize the insulin the body produces. The brief definition above thus suggest that there are two main types of diabetes called type 1 and type 2. For type 1 diabetes (also known as insulin-dependent or childhood-onset), there is insulin production deficiency in the body, which requires daily administration of insulin. Type 2 diabetes on the otherhand (known formally as non-insulin-dependent or adult-onset), occurs when the body cannot effectively use insulin produced.

In 2014, the World Health Organization (WHO) estimated the number of people with diabetes at 422 million, and in 2016, diabetes was the direct cause of 1.6 million deaths.

Grim statistics, isn't it?

0.0.3 2. PROJECT GOAL

In this project, my goal is to apply SIX machine learning algorithms namely; Logistic Regression, Decision tree, K-Nearest Neighbour, Support Vector Machine, Random Forest, and Naive Bayes to ascertain whether or not, on the basis of the features provided in the dataset, if applied to my machine learning model, a person would be found to have diabetes or not. The features for the prediction were determined by the National Institute of Diabetes, Digestive and Kidney Diseases.

0.0.4 3. DATASET

This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases. The objective of the dataset is to diagnostically predict whether or not a patient has diabetes, based on certain diagnostic measurements included in the dataset. 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. The datasets consists of several medical predictor variables and one target variable, Outcome. Predictor variables includes the number of pregnancies the patient has had, their BMI, insulin level, age, and so on.

0.0.5 4. METHODOLOGY: ALGORITHMS EMPLOYED

i. Logistic Regression

ii. Decision Tree

iii. KNN

iv. SVM

v. Random Forest

vi. Naive Bayes

0.0.6 5. DATA ASSESSMENT

We begin by importing the relevant libraries

[61]:
```
import pickle
import joblib
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline


from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn import datasets
from sklearn.metrics import accuracy_score
from sklearn import metrics

from sklearn.utils import resample
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report

from sklearn.linear_model import LogisticRegression
```

```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
```

[31]:
```python
# Loading dataset
df = pd.read_csv('diabetes.csv')
df.head().transpose()
```

[31]:

	0	1	2	3	4
Pregnancies	6.000	1.000	8.000	1.000	0.000
Glucose	148.000	85.000	183.000	89.000	137.000
BloodPressure	72.000	66.000	64.000	66.000	40.000
SkinThickness	35.000	29.000	0.000	23.000	35.000
Insulin	0.000	0.000	0.000	94.000	168.000
BMI	33.600	26.600	23.300	28.100	43.100
DiabetesPedigreeFunction	0.627	0.351	0.672	0.167	2.288
Age	50.000	31.000	32.000	21.000	33.000
Outcome	1.000	0.000	1.000	0.000	1.000

[3]:
```python
df.describe().transpose()
```

[3]:

	count	mean	std	min	25%	\
Pregnancies	768.0	3.845052	3.369578	0.000	1.00000	
Glucose	768.0	120.894531	31.972618	0.000	99.00000	
BloodPressure	768.0	69.105469	19.355807	0.000	62.00000	
SkinThickness	768.0	20.536458	15.952218	0.000	0.00000	
Insulin	768.0	79.799479	115.244002	0.000	0.00000	
BMI	768.0	31.992578	7.884160	0.000	27.30000	
DiabetesPedigreeFunction	768.0	0.471876	0.331329	0.078	0.24375	
Age	768.0	33.240885	11.760232	21.000	24.00000	
Outcome	768.0	0.348958	0.476951	0.000	0.00000	

	50%	75%	max
Pregnancies	3.0000	6.00000	17.00
Glucose	117.0000	140.25000	199.00
BloodPressure	72.0000	80.00000	122.00
SkinThickness	23.0000	32.00000	99.00
Insulin	30.5000	127.25000	846.00
BMI	32.0000	36.60000	67.10
DiabetesPedigreeFunction	0.3725	0.62625	2.42
Age	29.0000	41.00000	81.00
Outcome	0.0000	1.00000	1.00

[32]:
```python
df.columns
```

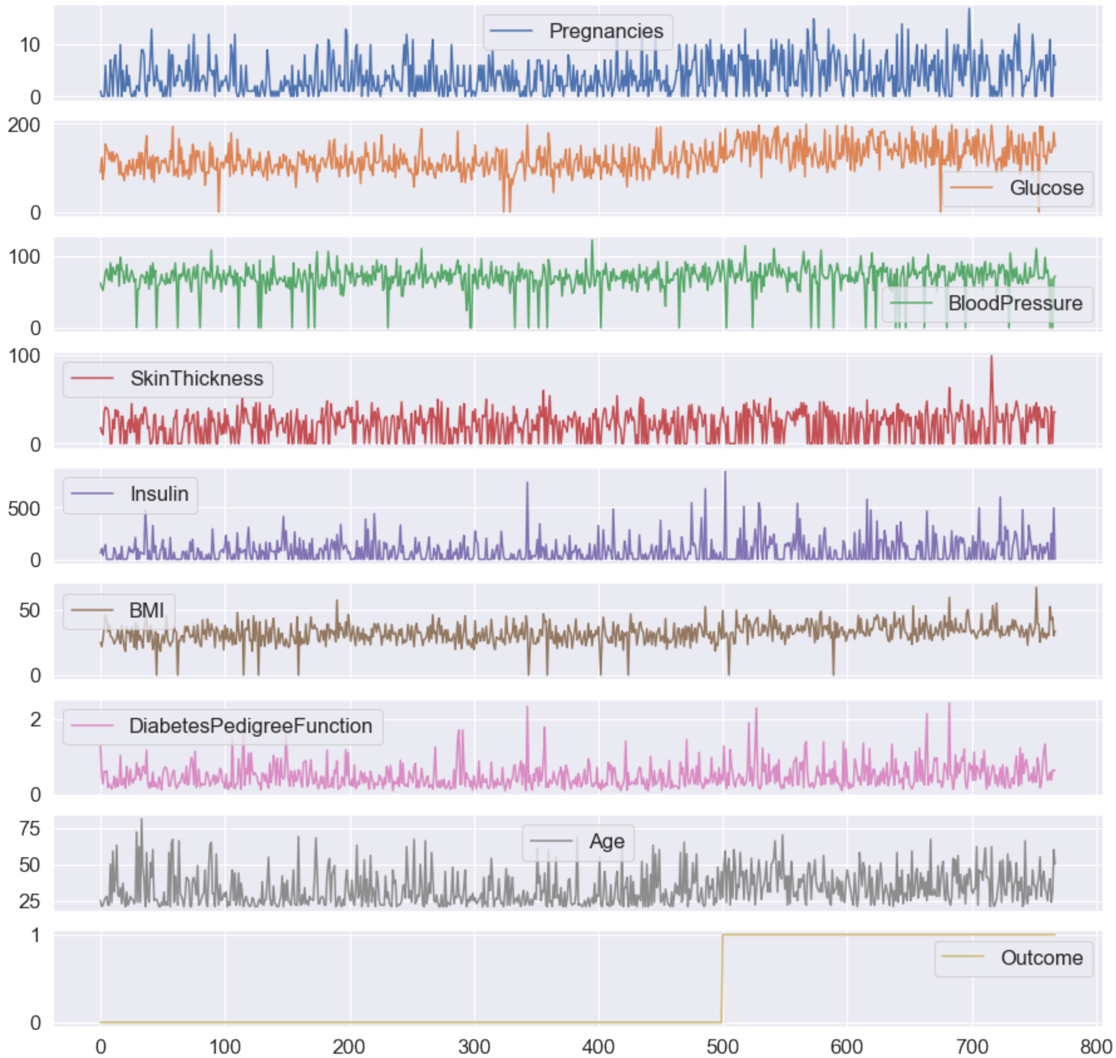
[32]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

[33]:
```
df.isnull().sum()
```

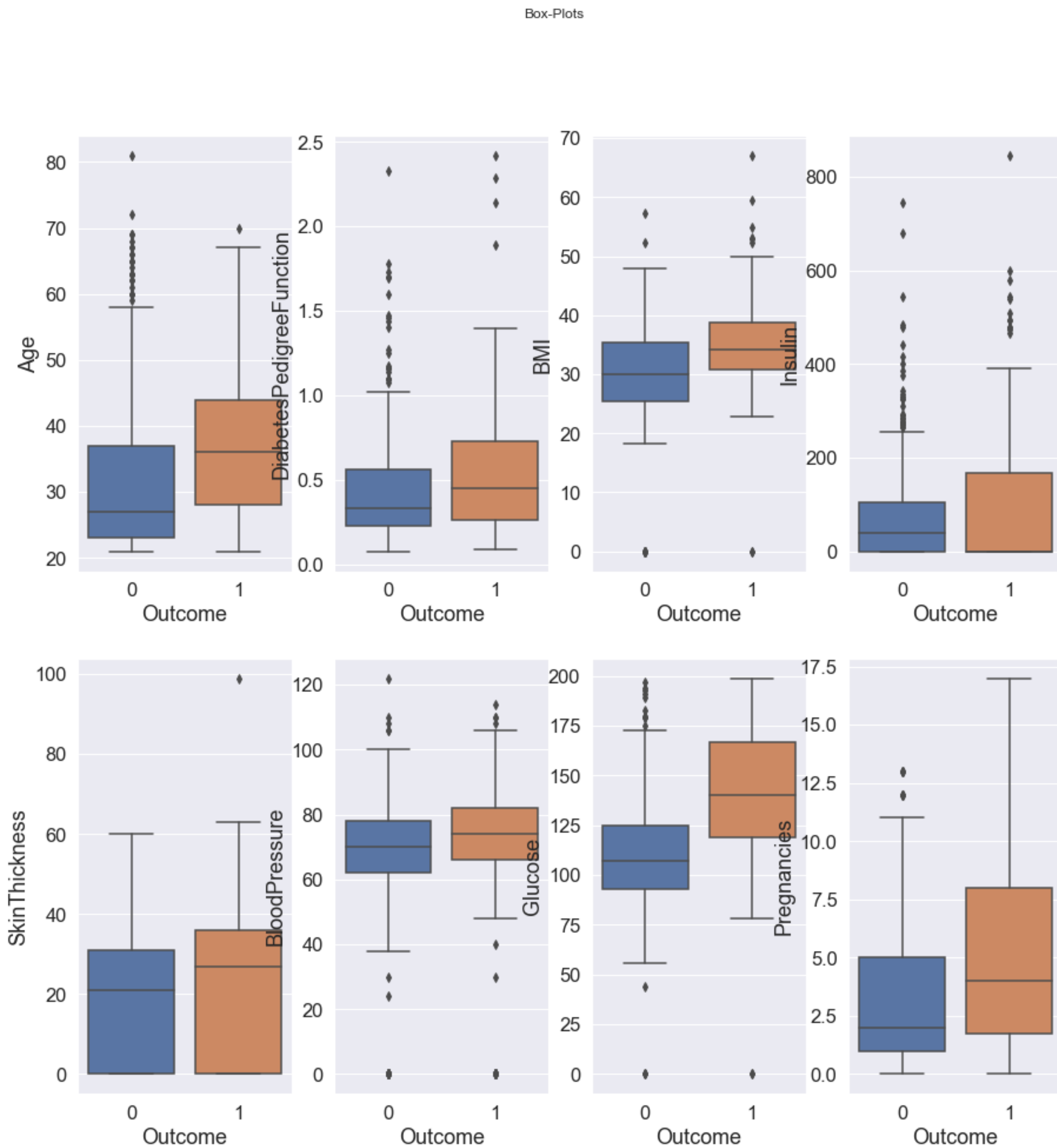
[33]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

0.0.7 6. EXPLORATORY DATA ANALYSIS

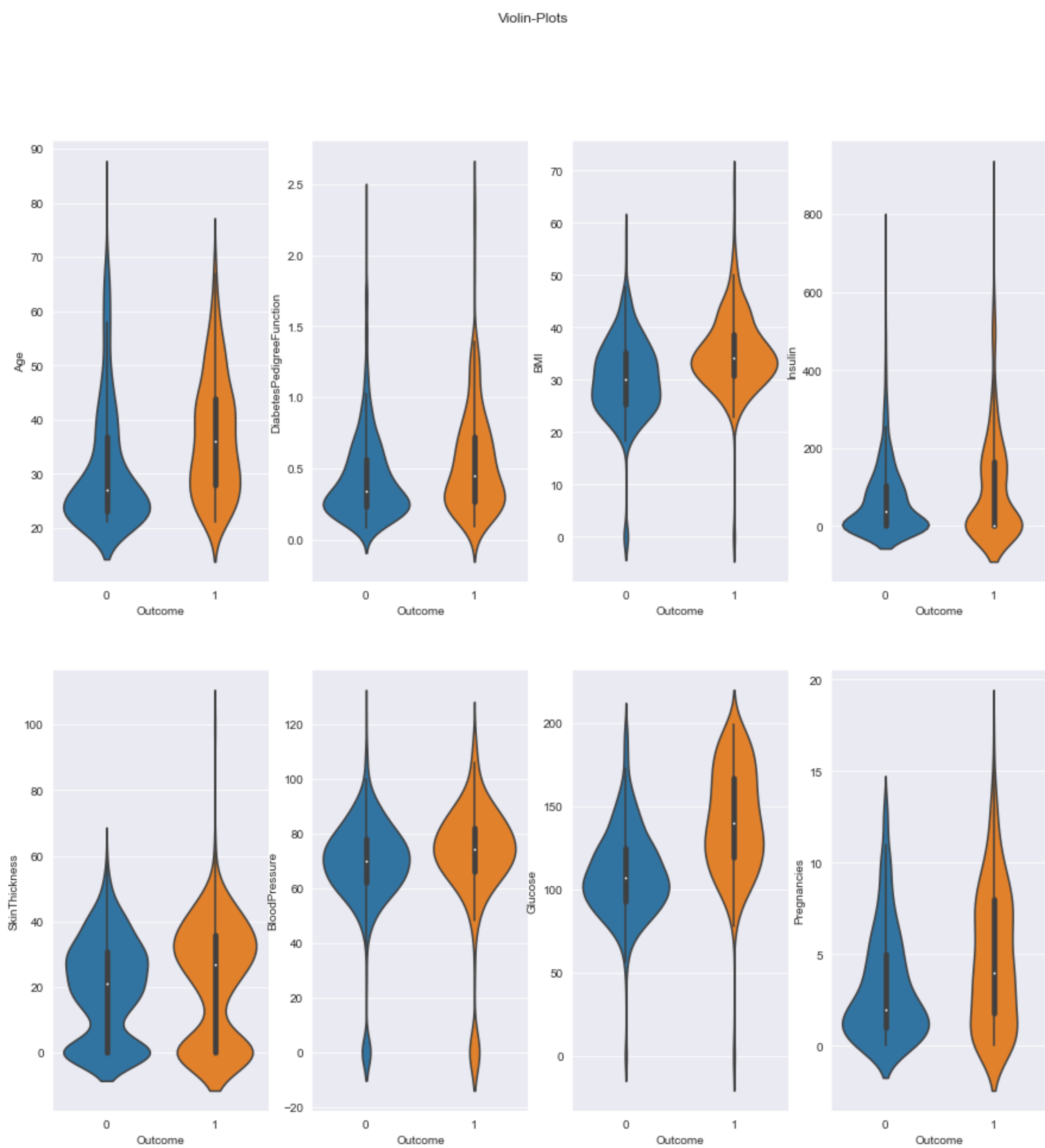
[34]:
```
df.sort_values(by=["Outcome"],inplace=True,ignore_index=True)
df.plot(figsize = (15,15), subplots = True)
plt.show()
```



[35]:
```
sns.set_style("darkgrid")
fig, axes = plt.subplots(2, 4, figsize=(15, 15))
fig.suptitle('Box-Plots')
continuous_variables = ['Pregnancies', 'Glucose', 'BloodPressure',␣
 ↪'SkinThickness', 'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age']
for i in range(0,2):
    for j in range(0,4):
        name =continuous_variables.pop()
        sns.boxplot(ax=axes[i, j], x='Outcome',y=name, data=df)
plt.show()
```



[8]:
```
sns.set_style("darkgrid")
fig, axes = plt.subplots(2, 4, figsize=(15, 15))
fig.suptitle('Violin-Plots')
continuous_variables = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age']
for i in range(0,2):
    for j in range(0,4):
        name =continuous_variables.pop()
        sns.violinplot(ax=axes[i, j], x='Outcome',y=name, data=df)
plt.show()
```




```
[9]: sns.set(font_scale=1.5)
     sns.pairplot(data = df, kind = "scatter", hue = "Outcome", aspect =1, height =␣
      ↪3)
     plt.show()
```

[13]:
```
corr_matrix=df.corr()
corr_matrix
```

[13]:

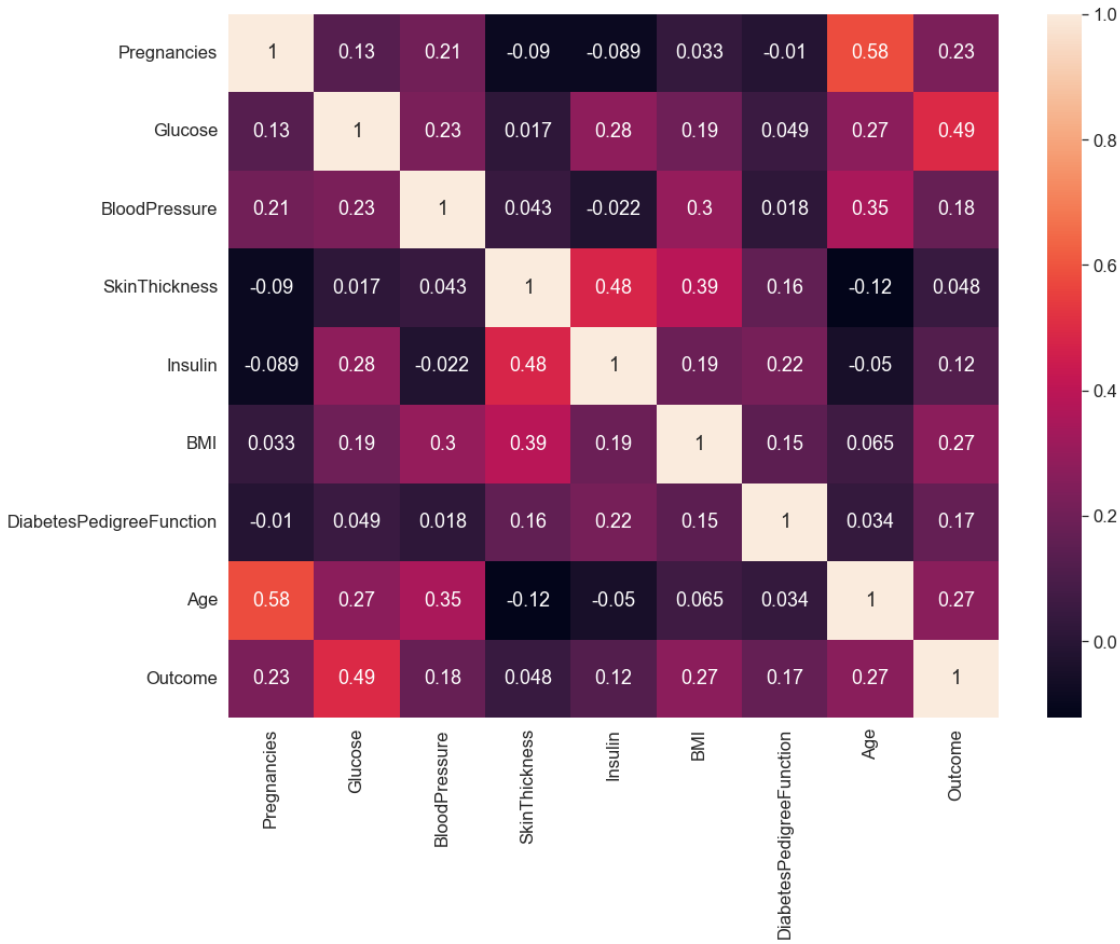
	Pregnancies	Glucose	BloodPressure	SkinThickness	\
Pregnancies	1.000000	0.131807	0.205941	-0.090282	
Glucose	0.131807	1.000000	0.226342	0.016667	
BloodPressure	0.205941	0.226342	1.000000	0.043437	
SkinThickness	-0.090282	0.016667	0.043437	1.000000	
Insulin	-0.089290	0.278115	-0.021548	0.479038	
BMI	0.033049	0.193795	0.295835	0.389314	
DiabetesPedigreeFunction	-0.010179	0.049141	0.017603	0.162642	
Age	0.581670	0.270411	0.347158	-0.121766	
Outcome	0.232391	0.494067	0.175838	0.047589	

```
                           Insulin       BMI  DiabetesPedigreeFunction  \
Pregnancies              -0.089290  0.033049                 -0.010179
Glucose                   0.278115  0.193795                  0.049141
BloodPressure            -0.021548  0.295835                  0.017603
SkinThickness             0.479038  0.389314                  0.162642
Insulin                   1.000000  0.186572                  0.216340
BMI                       0.186572  1.000000                  0.146864
DiabetesPedigreeFunction  0.216340  0.146864                  1.000000
Age                      -0.050083  0.064727                  0.034006
Outcome                   0.122651  0.272459                  0.169383

                               Age   Outcome
Pregnancies               0.581670  0.232391
Glucose                   0.270411  0.494067
BloodPressure             0.347158  0.175838
SkinThickness            -0.121766  0.047589
Insulin                  -0.050083  0.122651
BMI                       0.064727  0.272459
DiabetesPedigreeFunction  0.034006  0.169383
Age                       1.000000  0.265540
Outcome                   0.265540  1.000000
```

[14]:

```
fig, ax = plt.subplots(figsize=(16, 12))
sns.heatmap(df.corr(), annot=True)
plt.show()
```

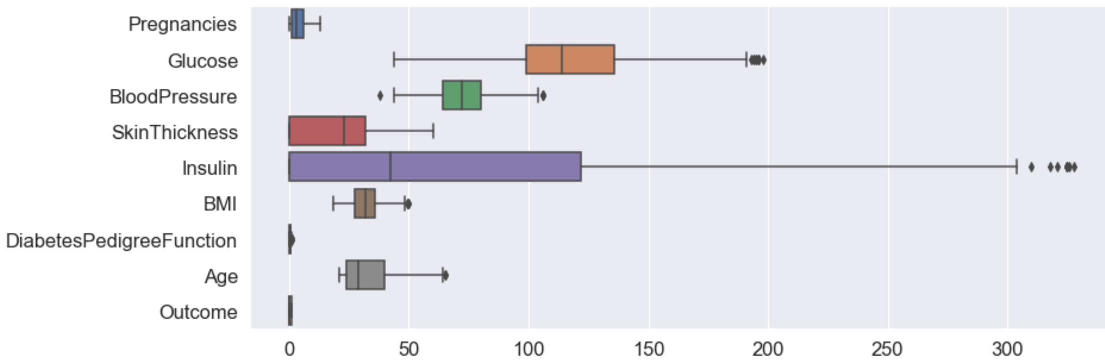


[36]:

```
#Eliminating Outliers with IQR Method
continuous_variables = ["Pregnancies", "Glucose", "BloodPressure",␣
↪"SkinThickness", "Insulin",
                        "BMI", "DiabetesPedigreeFunction", "Age"]
for i in range(0,8):
    Q1 = df[continuous_variables[i]].quantile(0.25)
    Q3 = df[continuous_variables[i]].quantile(0.75)
    IQR = Q3 - Q1
    lower_limit = Q1 - 1.5*IQR
    upper_limit = Q3 + 1.5*IQR
    print(lower_limit, upper_limit)
    df =␣
↪df[(df[continuous_variables[i]]>lower_limit)&(df[continuous_variables[i]]<upper_limit)]

plt.figure(figsize=(13,5))
sns.boxplot(data=df,orient='h')
plt.show()
```

```
-6.5 13.5
37.5 201.5
35.0 107.0
-49.5 82.5
-198.0 330.0
13.699999999999994 49.70000000000001
-0.30737499999999995 1.165625
-0.75 65.25
```



[37]:
```
df_majority = df[(df["Outcome"]==0)]
df_minority = df[(df["Outcome"]==1)]
df_minority_upsampled =␣
↪resample(df_minority,replace=True,n_samples=500,random_state=42)
df = pd.concat([df_minority_upsampled,df_majority])
df["Outcome"].value_counts()
```

[37]:
```
1    500
0    438
Name: Outcome, dtype: int64
```

Scaling the data

[38]:
```
scaler = StandardScaler()
scaler.fit_transform(df)
```

[38]:
```
array([[ 2.25616085,  0.47051134,  0.80497174, …,  0.35399794,
         2.17890062,  0.93594872],
       [-0.63453561,  0.2730881 , -0.26642023, …,  0.41168844,
        -1.01854741,  0.93594872],
       [-0.92360525,  1.81957008, -0.80211621, …, -0.47015214,
         0.35178746,  0.93594872],
       …,
       [ 0.81081262,  0.24018423,  0.98353706, …,  1.046284  ,
         0.2604318 , -1.06843461],
```

```
       [-0.34546596,  1.78666621, -0.80211621, …, -0.70503491,
        -0.74448044, -1.06843461],
       [ 1.67802156, -0.12175836,  0.44784108, …,  0.28806593,
         0.99127706, -1.06843461]])
```

[39]:
```python
X=df.drop('Outcome',axis='columns')
Y=df["Outcome"]
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.40,␣
↪random_state=4)
print("train data length:",len(X_train))
print("test data length:",len(X_test))
```

```
train data length: 562
test data length: 376
```

[40]:
```python
lr=LogisticRegression(C = 0.1, random_state = 42,
                      solver = 'liblinear')
dt=DecisionTreeClassifier()
rm=RandomForestClassifier()
gnb=GaussianNB()
knn = KNeighborsClassifier(n_neighbors=3)
svm = svm.SVC(kernel='linear')
```

[41]:
```python
for a,b in zip([lr,dt,knn,svm,rm,gnb],["Logistic Regression","Decision␣
↪Tree","KNN","SVM","Random Forest","Naive Bayes"]):
    a.fit(X_train,Y_train)
    prediction=a.predict(X_train)
    Y_pred=a.predict(X_test)
    score1=accuracy_score(Y_train,prediction)
    score=accuracy_score(Y_test,Y_pred)
    msg1="[%s] training data accuracy is : %f" % (b,score1)
    msg2="[%s] test data accuracy is : %f" % (b,score)
    print(msg1)
    print(msg2)
```

```
[Logistic Regression] training data accuracy is : 0.715302
[Logistic Regression] test data accuracy is : 0.712766
[Decision Tree] training data accuracy is : 1.000000
[Decision Tree] test data accuracy is : 0.845745
[KNN] training data accuracy is : 0.884342
[KNN] test data accuracy is : 0.792553
[SVM] training data accuracy is : 0.765125
[SVM] test data accuracy is : 0.787234
[Random Forest] training data accuracy is : 1.000000
[Random Forest] test data accuracy is : 0.888298
[Naive Bayes] training data accuracy is : 0.731317
[Naive Bayes] test data accuracy is : 0.736702
```

[46]:
```python
model_scores={'Logistic Regression':lr.score(X_test,Y_test),
             'KNN classifier':knn.score(X_test,Y_test),
             'Support Vector Machine':svm.score(X_test,Y_test),
             'Random forest':rm.score(X_test,Y_test),
              'Decision tree':dt.score(X_test,Y_test),
              'Naive Bayes':gnb.score(X_test,Y_test)
             }
model_scores
```

[46]:
```
{'Logistic Regression': 0.7127659574468085,
 'KNN classifier': 0.7925531914893617,
 'Support Vector Machine': 0.7872340425531915,
 'Random forest': 0.8882978723404256,
 'Decision tree': 0.8457446808510638,
 'Naive Bayes': 0.7367021276595744}
```

[50]:
```python
rm_y_preds = rm.predict(X_test)
print(classification_report(Y_test,rm_y_preds))
```

```
              precision    recall  f1-score   support

           0       0.97      0.79      0.87       180
           1       0.83      0.98      0.90       196

    accuracy                           0.89       376
   macro avg       0.90      0.88      0.89       376
weighted avg       0.90      0.89      0.89       376
```

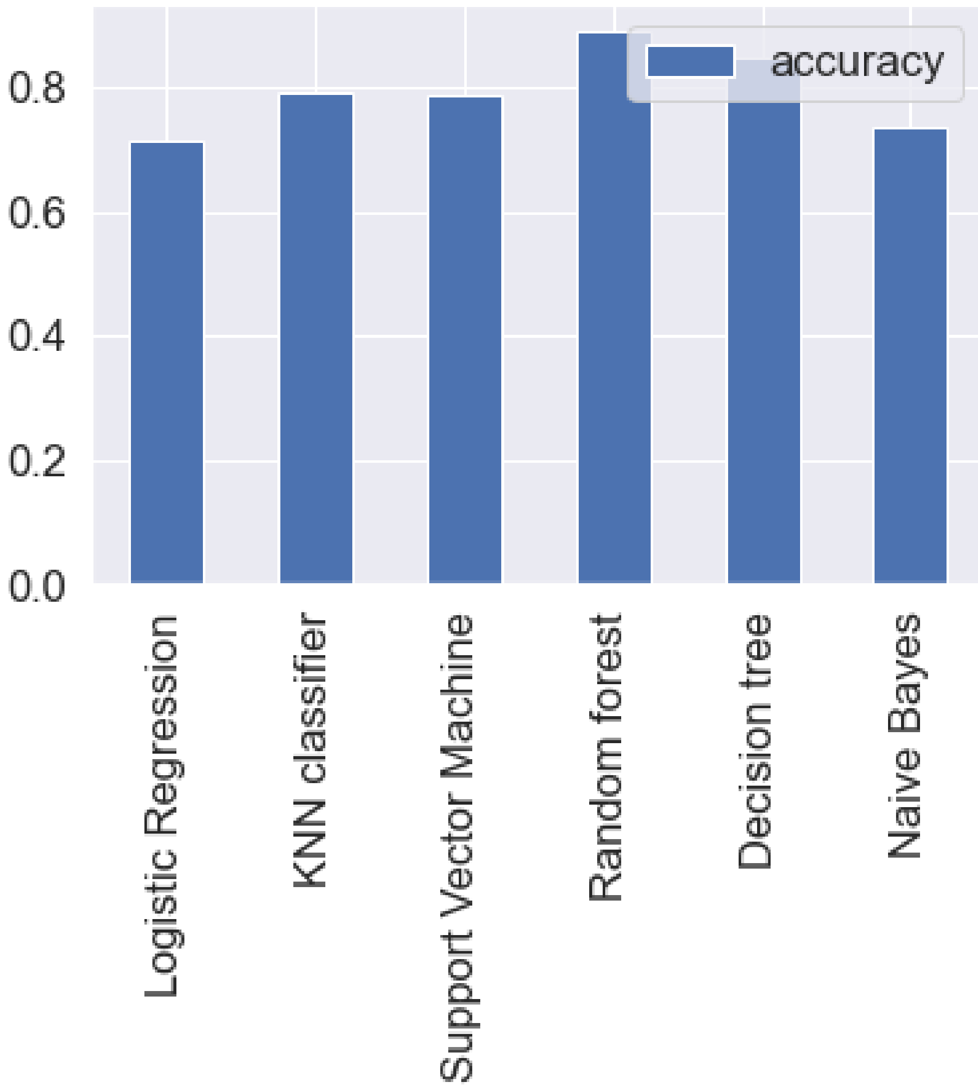
[51]:
```python
model_compare=pd.DataFrame(model_scores,index=['accuracy'])
model_compare
```

[51]:
```
          Logistic Regression  KNN classifier  Support Vector Machine  \
accuracy             0.712766        0.792553                0.787234

          Random forest  Decision tree  Naive Bayes
accuracy       0.888298       0.845745     0.736702
```

[55]:
```python
model_compare.T.plot(kind='bar')
```

[55]: <AxesSubplot:>

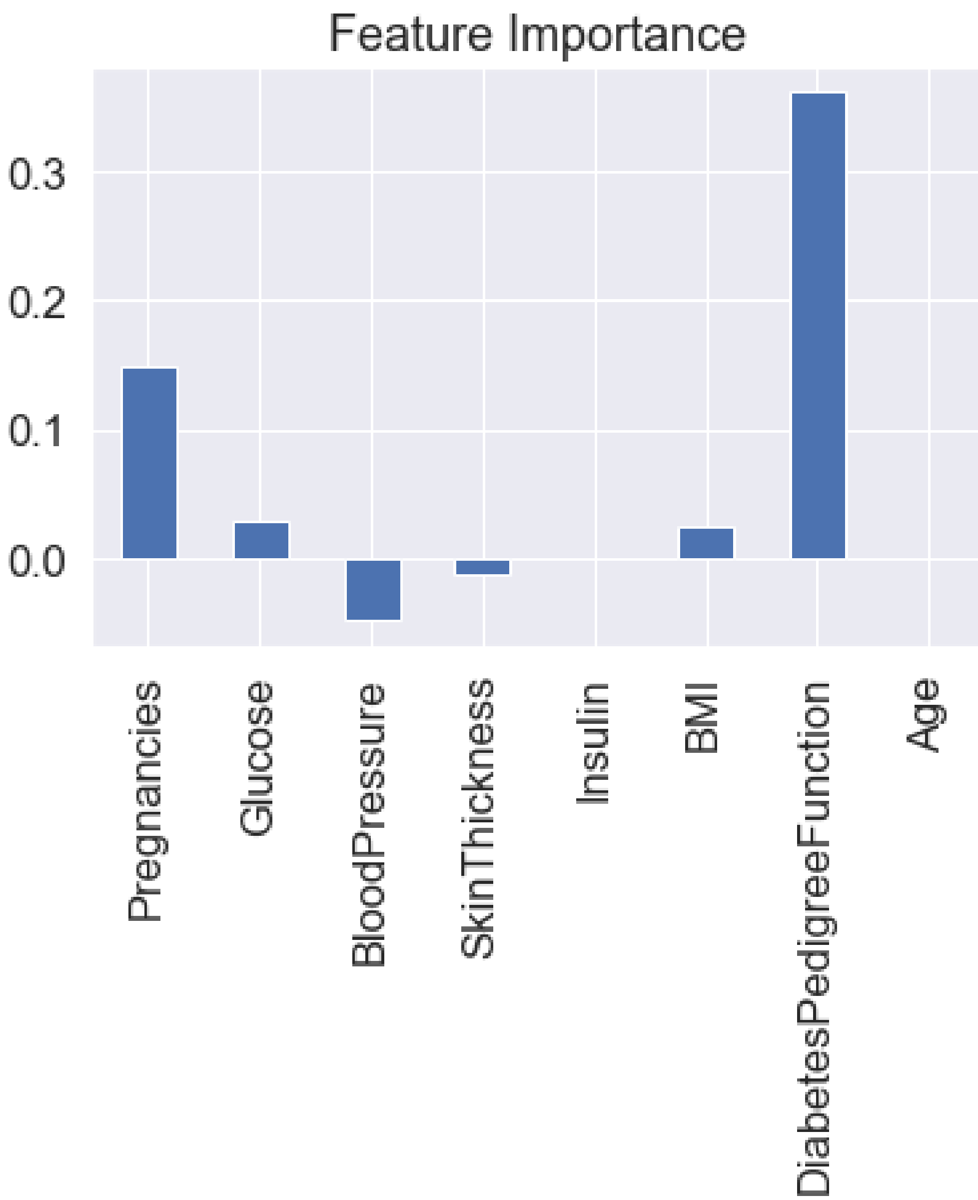


[57]:
```
feature_dict=dict(zip(df.columns,list(lr.coef_[0])))
feature_dict
```

[57]:
```
{'Pregnancies': 0.14824874880299124,
 'Glucose': 0.028667239813555928,
 'BloodPressure': -0.04771083398624526,
 'SkinThickness': -0.012513640119956447,
 'Insulin': 0.00036355736098703516,
 'BMI': 0.025059050345751687,
 'DiabetesPedigreeFunction': 0.3611879907767143,
 'Age': -0.00032668554302465l}
```

[58]:
```
feature_df=pd.DataFrame(feature_dict,index=[0])
feature_df.T.plot(kind="bar",legend=False,title="Feature Importance")
```

[58]: <AxesSubplot:title={'center':'Feature Importance'}>



[60]:
```
saved_model = pickle.dumps(lr)
lr_from_pickle = pickle.loads(saved_model)
lr_from_pickle.predict(X_test)
```

[60]:
```
array([0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1,
       1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0,
       1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1,
       0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0,
       1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1,
       0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1,
       0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0,
       1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0,
       1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0,
       1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0,
       0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0,
       0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1,
       0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1,
       1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1,
       1, 1])
```

[62]:
```
joblib.dump(lr , 'model_lr')
m_jlib = joblib.load('model_lr')
m_jlib.predict(X_test)
```

[62]:
```
array([0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1,
       1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0,
       1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1,
       0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0,
       1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1,
       0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1,
       0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0,
       1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0,
       1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0,
       1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0,
       0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0,
       0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1,
       0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1,
       1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1,
       1, 1])
```

Summary:

Model accuracy Logistic Regression - 71.3% Decision tree - 84.6% K-Nearest Neighbour - 79.3% Support Vector Machine - 78.7% Random Forest - 88.83% Naive Bayes - 73.7%

In comparing the six Machine learning algorithms applied in this project, Random Forest algorithm appears to be the most suitable for the prediction as it is the algorithm that recorded the highest accuracy score of 88.83%.

[ ]:

```

```