```
In [841]:
           import matplotlib.pyplot as plt
              import numpy as np
              import pandas as pd
              import json
              import requests
              from collections import Counter
              from sklearn.impute import KNNImputer
              import numpy as np
              from sklearn.datasets import make_blobs
              from sklearn.preprocessing import StandardScaler
              import matplotlib.pyplot as plt
              import seaborn as sn
              import matplotlib.pyplot as plt
              import numpy as np
              import matplotlib.pyplot as plt
              import seaborn as sns
              from bioinfokit.analys import stat
              from sklearn import metrics
              from sklearn.metrics import confusion_matrix
              from sklearn.svm import SVC
              from sklearn.tree import DecisionTreeClassifier
              from sklearn.ensemble import RandomForestClassifier
              from sklearn.preprocessing import StandardScaler
              from sklearn.decomposition import PCA
              from sklearn.linear_model import LogisticRegression
              pd.set_option('display.max_columns', 500)
              df = pd.read_csv('Pima.csv')
              df
```

Out[841]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFund
	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	2
	763	10	101	76	48	180	32.9	C
	764	2	122	70	27	0	36.8	C
	765	5	121	72	23	112	26.2	(
	766	1	126	60	0	0	30.1	(
	767	1	93	70	31	0	30.4	(

Overall understanding of the data

0 / 50067									
Out[836]:	Pre	gnancies G	lucose	BloodPressure	SkinThickness	Insulin	BMI Di	abetesPedigree	Function
	0	6	148	72	35	0	33.6		0.6
	1	1	85	66	29	0	26.6		0.3
	2	8	183	64	0	0	23.3		0.6
	3	1	89	66	23	94	28.1		0.1
	4	0	137	40	35	168	43.1		2.2
	4)
In [842]: ▶	df.dty	pes							
Out[842]:	Pregna			int					
	Glucos BloodP	e ressure		int int					
		ickness		int					
	Insuli	n		int					
	BMI Diabet	esPedigree	eFunctio	float on float					
	Age	_		int	64				
	Outcom dtype:	e object		int	64				
In [843]: ▶	df.des	cribe()							
Out[843]:		Pregnancies	s Glu	cose BloodPr	essure SkinThio	kness	Insuli	n BMI	Diabe
	count	768.00000	768.00	0000 768.0	000000 768.0	000000	768.00000	768.000000	
	mean	3.845052	2 120.89	4531 69. ⁻	105469 20.5	536458	79.79947	9 31.992578	
	std	3.369578	31.97	2618 19.3	355807 15.9	952218	115.24400	2 7.884160	
	min	0.00000	0.00	0.00	0.00000	000000	0.00000	0.000000	
	25%	1.00000	99.00	0000 62.0	0.00000	000000	0.00000	27.300000	
	50%	3.000000	0 117.00	0000 72.0	000000 23.0	000000	30.50000	32.000000	
	75%	6.00000	140.25	0000 80.0	000000 32.0	000000	127.25000	36.600000	
	max	17.00000	199.00	0000 122.0	000000 99.0	000000	846.00000	67.100000	
	4								•

Handle missing values. There is no standard procedure of missing value imputation. For simplicity, follow the procedure below:

• Remove the rows containing the missing values if less than 5% of values are missing in a c

Out[844]: (768, 9)

• If the percentage of missing values is between 5 % and 30%, fill the missing data with the Remove the feature if more than 30% of its values are missing

```
In [845]:
              df[['Glucose ','BloodPressure','SkinThickness','Insulin ','BMI']] = df[['Glu
              print(df.isnull().sum())
                                               0
               Pregnancies
              Glucose
                                               5
                                              35
               BloodPressure
              SkinThickness
                                             227
                                             374
               Insulin
               BMI
                                              11
                                               0
              DiabetesPedigreeFunction
                                               0
              Age
              Outcome
               dtype: int64
In [846]:
            ▶ | p=df.isnull().sum() / df.shape[0]
   Out[846]: Pregnancies
                                             0.000000
               Glucose
                                             0.006510
               BloodPressure
                                             0.045573
              SkinThickness
                                             0.295573
               Insulin
                                             0.486979
               BMI
                                             0.014323
              DiabetesPedigreeFunction
                                             0.000000
                                             0.000000
              Age
              Outcome
                                             0.000000
               dtype: float64
```

From the result above we note that these features have more than 05% missing data -Remove the rows containing the missing values if less than 5% of values are missing in a column, the column Bloodpressure and BMI has less than 5% missing , So we will proceed to delete those missing rows

Use KNN to input the missing data

```
In [848]:
           ₩ # define imputer
              imputer = KNNImputer()
              # fit on the dataset
              imputer.fit(df)
              # transform the dataset
              df_filled = imputer.transform(df)
              df_filled = pd.DataFrame(df_filled)
              #df_filled.info()
              df2 = df_filled.rename({0: 'Pregnancies', 1: 'Glucose',2:'BloodPressure',3:'S
                      DiabetesPedigreeFunction
                                                  Age Outcome
              df2.head()
              # print total missing
              df2.isnull().sum()
   Out[848]: Pregnancies
              Glucose
                                0
              BloodPressure
                                0
              SkinThickness
                                0
              Insulin
                                0
              BMI
                                0
              DBF
                                0
              Age
                                0
              Outcome
              dtype: int64
```

Find outliers in data

```
In [849]:
           ▶ plt.figure(figsize=(18,35))
              plt.subplot(8,2,3)
              sns.distplot(df2['Glucose'])
              plt.subplot(8,2,4)
              sns.boxplot(df2['Glucose'])
              plt.subplot(8,2,5) #histogram
              sns.distplot(df2['BloodPressure'])
              plt.subplot(8,2,6)
              sns.boxplot(df2['BloodPressure'])
              plt.subplot(8,2,7) #histogram
              sns.distplot(df2['SkinThickness'])
              plt.subplot(8,2,8)
              sns.boxplot(df2['SkinThickness'])
              plt.subplot(8,2,9) #histogram
              sns.distplot(df2['Insulin'])
              plt.subplot(8,2,10)
              sns.boxplot(df2['Insulin'])
              plt.subplot(8,2,11) #histogram
              sns.distplot(df2['BMI'])
              plt.subplot(8,2,12)
              sns.boxplot(df2['BMI'])
              plt.subplot(8,2,13) #histogram
              sns.distplot(df2['DBF'])
              plt.subplot(8,2,14)
              sns.boxplot(df2['DBF'])
              plt.show()
```

C:\Users\merie\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figur e-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

warnings.warn(msg, FutureWarning)

C:\Users\merie\anaconda3\lib\site-packages\seaborn_decorators.py:36: Fut ureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing othe r arguments without an explicit keyword will result in an error or misint erpretation.

warnings.warn(

C:\Users\merie\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figur e-level function with similar flexibility) or `histplot` (an axes-level f unction for histograms).

warnings.warn(msg, FutureWarning)

C:\Users\merie\anaconda3\lib\site-packages\seaborn_decorators.py:36: Fut

```
In [850]:
           ▶ from collections import Counter
              def detect outliers(df2,features):
                  outlier indices = []
                  for c in features:
                      # 1st quartile
                      Q1 = np.percentile(df2[c],25)
                      # 3rd quartile
                      Q3 = np.percentile(df2[c],75)
                       # IQR
                      IQR = Q3 - Q1
                       # Outlier step
                      outlier_step = IQR * 1.5
                      # detect outlier and their indeces
                      outlier_list_col = df2[(df2[c] < Q1 - outlier_step) | (df2[c] > Q3 +
                      # store indeces
                      outlier indices.extend(outlier list col)
                  outlier_indices = Counter(outlier_indices)
                  multiple outliers = list(i for i, v in outlier indices.items() if v > 2)
                  return multiple_outliers
In [851]:
           ▶ df2.loc[detect_outliers(df2,[ 'Pregnancies', 'Glucose', 'BloodPressure', 'Skir
   Out[851]:
                    Pregnancies Glucose BloodPressure SkinThickness Insulin
                                                                        BMI DBF Age Outcome
               418
                           0.0
                                 180.0
                                               78.0
                                                            63.0
                                                                   14.0 59.4 2.42 25.0
                                                                                            1.0
              df2 = df2.drop(detect_outliers(df2,[ 'Pregnancies','Glucose', 'BloodPressure
In [852]:
```

Out[853]

]:	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DBF	Age	Outcom
0	6.0	148.0	72.0	35.0	169.0	33.6	0.627	50.0	1.
1	1.0	85.0	66.0	29.0	58.6	26.6	0.351	31.0	0.
2	8.0	183.0	64.0	25.8	164.6	23.3	0.672	32.0	1.
3	1.0	89.0	66.0	23.0	94.0	28.1	0.167	21.0	0.
4	0.0	137.0	40.0	35.0	168.0	43.1	2.288	33.0	1.
718	10.0	101.0	76.0	48.0	180.0	32.9	0.171	63.0	0.
719	2.0	122.0	70.0	27.0	165.0	36.8	0.340	27.0	0.
720	5.0	121.0	72.0	23.0	112.0	26.2	0.245	30.0	0.
721	1.0	126.0	60.0	35.2	134.2	30.1	0.349	47.0	1.
722	1.0	93.0	70.0	31.0	66.6	30.4	0.315	23.0	0.

702 rows × 9 columns

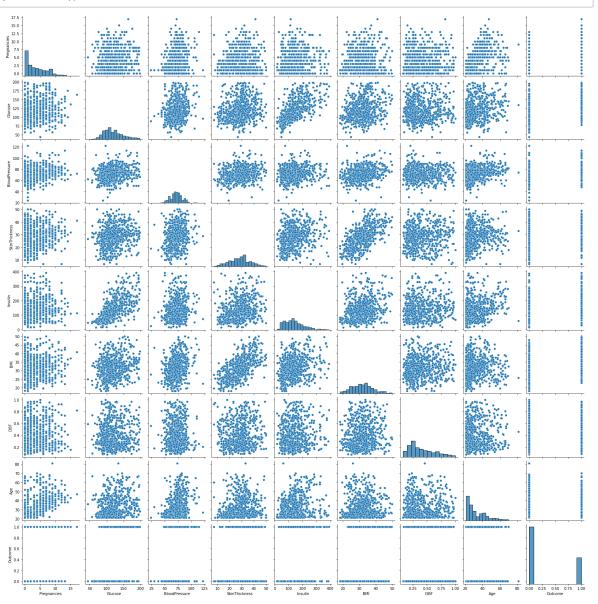
In [854]: ► df2.drop(df2.index[df2['DBF'] > 1.0], inplace = True)
#df2

Out[854]:		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	вмі	DBF	Age	Outcom
	0	6.0	148.0	72.0	35.0	169.0	33.6	0.627	50.0	1.
	1	1.0	85.0	66.0	29.0	58.6	26.6	0.351	31.0	0.
	2	8.0	183.0	64.0	25.8	164.6	23.3	0.672	32.0	1.
	3	1.0	89.0	66.0	23.0	94.0	28.1	0.167	21.0	0.
	5	5.0	116.0	74.0	20.6	102.8	25.6	0.201	30.0	0.
		•••								
	718	10.0	101.0	76.0	48.0	180.0	32.9	0.171	63.0	0.
	719	2.0	122.0	70.0	27.0	165.0	36.8	0.340	27.0	0.
	720	5.0	121.0	72.0	23.0	112.0	26.2	0.245	30.0	0.
	721	1.0	126.0	60.0	35.2	134.2	30.1	0.349	47.0	1.
	722	1.0	93.0	70.0	31.0	66.6	30.4	0.315	23.0	0.

656 rows × 9 columns

```
df2.drop(df2.index[df2['BMI'] > 50], inplace = True)
In [856]:
                  #df2
                 df2.describe()
In [857]:
    Out[857]:
                          Pregnancies
                                         Glucose
                                                   BloodPressure
                                                                   SkinThickness
                                                                                       Insulin
                                                                                                       BMI
                   count
                           644.000000
                                        644.00000
                                                       644.000000
                                                                       644.000000
                                                                                   644.000000
                                                                                               644.000000
                                                                                                            644.000
                             3.900621
                                        119.76087
                                                        72.049689
                                                                        28.339441
                                                                                   141.493478
                                                                                                 31.876708
                                                                                                              0.407
                   mean
                                                                                                              0.219
                             3.331279
                                         29.55121
                                                        12.166318
                                                                         8.612862
                                                                                    73.210924
                                                                                                  6.345578
                     std
                    min
                             0.000000
                                         44.00000
                                                        24.000000
                                                                         7.000000
                                                                                    15.000000
                                                                                                 18.200000
                                                                                                              0.078
                    25%
                             1.000000
                                         99.00000
                                                        64.000000
                                                                        22.700000
                                                                                    87.450000
                                                                                                 27.300000
                                                                                                              0.237
                    50%
                             3.000000
                                        114.00000
                                                        72.000000
                                                                        29.000000
                                                                                   130.000000
                                                                                                 32.000000
                                                                                                              0.346
                             6.000000
                                                                        33.450000
                                                                                                 35.800000
                                                                                                              0.557
                    75%
                                        138.00000
                                                        80.000000
                                                                                   181.850000
                                        198.00000
                            17.000000
                                                                        50.000000
                                                                                   392.000000
                                                                                                 50.000000
                                                                                                              0.997
                                                       122.000000
                    max
                                                                                                                 \blacktriangleright
  In [ ]:
```

Relevant Feature



Correlation



BloodPressure SkinThickness

Glucose

Null Hypothesis

Pregnancies

Most of the studies related on the correlation coeffecient, the chi square is processed in my analysis to wether follow the reuslt of the coeffecient or not of the less correlated variables : preganancies , Blood pressure, Age , sckinthickness

вы

DBF

Age

Outcome

Chi-squared test for independence

Test	Df	Chi-square	P-value		
Pearson	43	52.0125	0.163052		
Log-likelihood	43	62.0722	0.0298755		

Chi-squared test for independence

Test	Df	Chi-square	P-value
Pearson	50	130.895	3.61438e-09
Log-likelihood	50	136.389	6.08482e-10

Chi-squared test for independence

Test	Df	Chi-square	P-value
Pearson	16	59.8596	5.52651e-07
Log-likelihood	16	60.2529	4.7443e-07

Chi-squared test for independence

Chi-squared test for independence

if chi square > critical value: conclusion = "Null Hypothesis is rejected."

From the above data we can see that most of the data has outliers except Glucose

```
In [960]:  X = df2[[ 'Glucose', 'Pregnancies', 'Age', 'Insulin', 'BMI']]
y = df2['Outcome']
```

In [961]: ► X.describe()

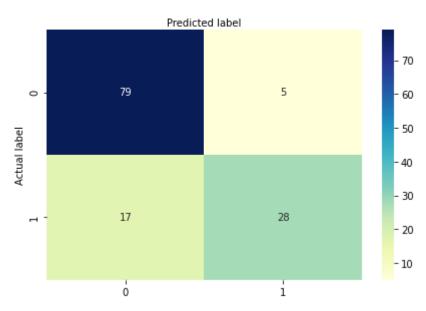
\sim		$\Gamma \cap C$	17	
U	uι	סצ ו	т і	

	Glucose	Pregnancies	Age	Insulin	ВМІ
count	644.00000	644.000000	644.000000	644.000000	644.000000
mean	119.76087	3.900621	33.133540	141.493478	31.876708
std	29.55121	3.331279	11.749228	73.210924	6.345578
min	44.00000	0.000000	21.000000	15.000000	18.200000
25%	99.00000	1.000000	24.000000	87.450000	27.300000
50%	114.00000	3.000000	29.000000	130.000000	32.000000
75%	138.00000	6.000000	40.250000	181.850000	35.800000
max	198.00000	17.000000	81.000000	392.000000	50.000000

Model on imbalanced Dataset without any scaling

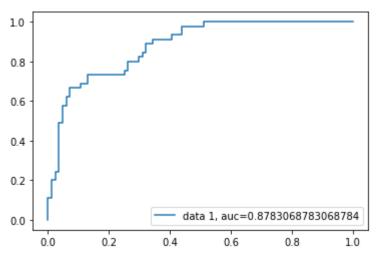
Logistique regression

Out[875]: Text(0.5, 257.44, 'Predicted label')



```
In [876]:  print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
  print("Precision:",metrics.precision_score(y_test, y_pred))
  print("Recall:",metrics.recall_score(y_test, y_pred))
```

Accuracy: 0.8294573643410853 Precision: 0.8484848484848485 Recall: 0.62222222222222

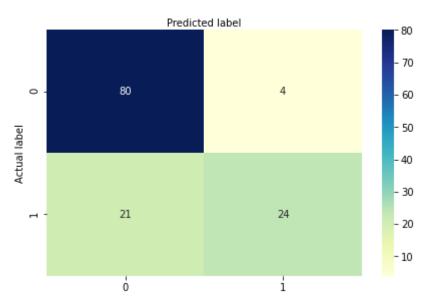


SVM

```
In [880]:
              cm1 = confusion matrix(y test, y pred1)
              print (cm)
              [[80 4]
               [21 24]]
In [881]:
           M | cnf_matrix1 = metrics.confusion_matrix(y_test, y_pred1)
              class names=[0,1] # name of classes
              fig, ax = plt.subplots()
              tick_marks = np.arange(len(class_names))
              plt.xticks(tick marks, class names)
              plt.yticks(tick_marks, class_names)
              # create heatmap
              sns.heatmap(pd.DataFrame(cnf matrix), annot=True, cmap="YlGnBu" ,fmt='g')
              ax.xaxis.set label position("top")
              plt.tight_layout()
              plt.title('Confusion matrix', y=1.1)
              plt.ylabel('Actual label')
              plt.xlabel('Predicted label')
```

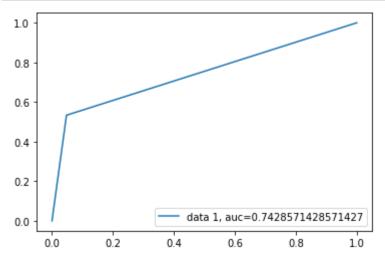
Out[881]: Text(0.5, 257.44, 'Predicted label')

Confusion matrix



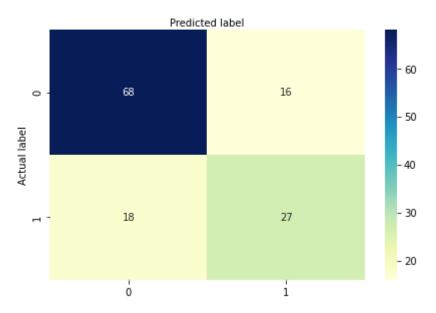
```
In [882]:  print("Accuracy:",metrics.accuracy_score(y_test, y_pred1))
  print("Precision:",metrics.precision_score(y_test, y_pred1))
  print("Recall:",metrics.recall_score(y_test, y_pred1))
```

Accuracy: 0.8062015503875969 Precision: 0.8571428571428571 Recall: 0.5333333333333333



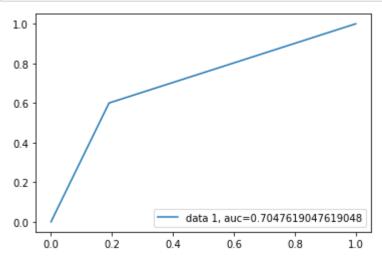
Decision tree

Out[885]: Text(0.5, 257.44, 'Predicted label')



Accuracy: 0.7364341085271318 Precision: 0.627906976744186

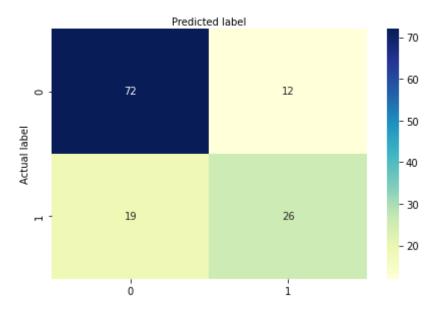
Recall: 0.6



Random Forest

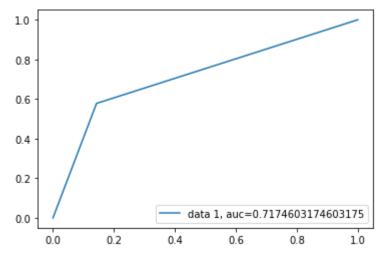
```
In [889]: N cnf_matrix3 = metrics.confusion_matrix(y_test, y_pred3)
    class_names=[0,1] # name of classes
    fig, ax = plt.subplots()
    tick_marks = np.arange(len(class_names))
    plt.xticks(tick_marks, class_names)
    plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[889]: Text(0.5, 257.44, 'Predicted label')



```
In [890]:  print("Accuracy:",metrics.accuracy_score(y_test, y_pred3))
  print("Precision:",metrics.precision_score(y_test, y_pred3))
  print("Recall:",metrics.recall_score(y_test, y_pred3))
```

Accuracy: 0.7596899224806202 Precision: 0.6842105263157895 Recall: 0.577777777777777



Scaling the data

```
In [892]:

X = df2[[ 'Glucose', 'Pregnancies', 'Age', 'Insulin', 'BMI']]

              y = df2['Outcome']
In [893]:

    Scaler=StandardScaler()

              Scaler.fit(X)
   Out[893]: StandardScaler()
In [894]:
           X= Scaler.transform(X)
              Χ
   Out[894]: array([[ 0.95634261, 0.63069197, 1.4366536, 0.37600813, 0.27178476],
                     [-1.17720695, -0.87139985, -0.18173099, -1.1331357, -0.83220308],
                     [ 2.14164792, 1.23152869, -0.09655286, 0.31586109, -1.35265449],
                     [ 0.04196423, 0.3302736 , -0.26690913, -0.40316939, -0.8952881 ],
                     [0.21129356, -0.87139985, 1.18111919, -0.09970025, -0.28020916],
                     [-0.90628002, -0.87139985, -0.86315608, -1.02377745, -0.23289539]])
In [895]:
           ▶ from sklearn.model selection import train test split
              X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,ran
```

Model on imbalanced Dataset with scaling

Logisitique regression on imbalanced dataset

with scaling

```
In [896]:

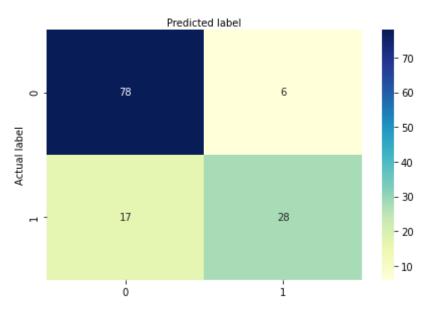
    ₩ instantiate the model (using the default parameters)

             classifier4 = LogisticRegression()
             # fit the model with data
             classifier4.fit(X_train,y_train)
            y pred4=classifier4.predict(X test)
          In [897]:
             class_names=[0,1] # name of classes
             fig, ax = plt.subplots()
             tick_marks = np.arange(len(class_names))
             plt.xticks(tick marks, class names)
             plt.yticks(tick_marks, class_names)
             # create heatmap
             sns.heatmap(pd.DataFrame(cnf matrix), annot=True, cmap="YlGnBu" ,fmt='g')
             ax.xaxis.set_label_position("top")
             plt.tight layout()
             plt.title('Confusion matrix', y=1.1)
```

Out[897]: Text(0.5, 257.44, 'Predicted label')

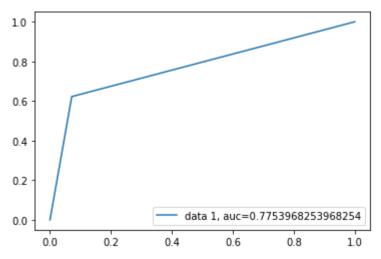
plt.ylabel('Actual label')
plt.xlabel('Predicted label')

Confusion matrix



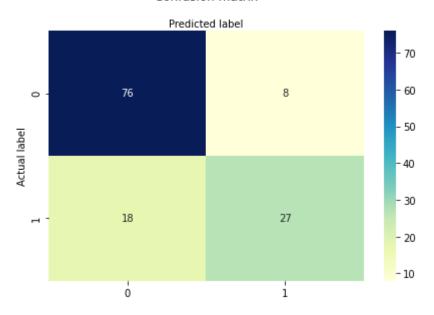
```
In [899]:  print("Accuracy:",metrics.accuracy_score(y_test, y_pred4))
  print("Precision:",metrics.precision_score(y_test, y_pred4))
  print("Recall:",metrics.recall_score(y_test, y_pred4))
```

Accuracy: 0.8217054263565892 Precision: 0.8235294117647058 Recall: 0.62222222222222



SVM

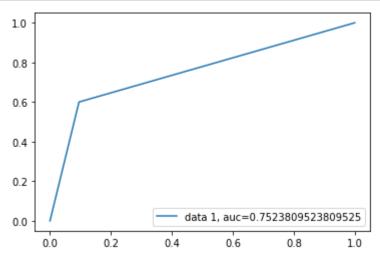
Out[902]: Text(0.5, 257.44, 'Predicted label')



```
In [903]:  print("Accuracy:",metrics.accuracy_score(y_test, y_pred5))
  print("Precision:",metrics.precision_score(y_test, y_pred5))
  print("Recall:",metrics.recall_score(y_test, y_pred5))
```

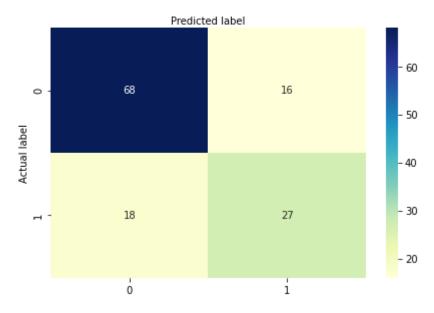
Accuracy: 0.7984496124031008 Precision: 0.7714285714285715

Recall: 0.6



Decision Tree

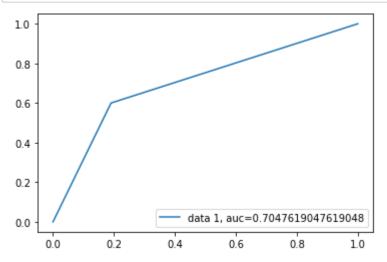
Out[906]: Text(0.5, 257.44, 'Predicted label')



```
In [907]:  print("Accuracy:",metrics.accuracy_score(y_test, y_pred6))
print("Precision:",metrics.precision_score(y_test, y_pred6))
print("Recall:",metrics.recall_score(y_test, y_pred6))
```

Accuracy: 0.7364341085271318 Precision: 0.627906976744186

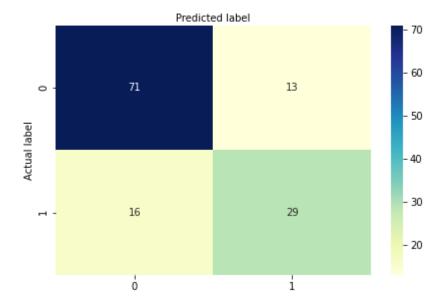
Recall: 0.6



Random Forest

```
In [910]: I
```

Out[910]: Text(0.5, 257.44, 'Predicted label')



```
In [911]:

▶ | print("Accuracy:",metrics.accuracy_score(y_test, y_pred7))
               print("Precision:",metrics.precision_score(y_test, y_pred7))
               print("Recall:", metrics.recall score(y test, y pred7))
               Accuracy: 0.7751937984496124
               Precision: 0.6904761904761905
               Recall: 0.64444444444445
In [912]:
              y pred proba7 =classifier7.predict(X test)
               fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_proba7)
               auc = metrics.roc_auc_score(y_test, y_pred_proba7)
               plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
               plt.legend(loc=4)
               plt.show()
                1.0
                0.8
                0.6
                0.4
                0.2
                                        data 1, auc=0.7448412698412697
                0.0
                             0.2
                                             0.6
                    0.0
                                     0.4
                                                      0.8
                                                              1.0
```

Balancing the dataset with the undersampling technique

```
In [914]:
            class 0 under = class 0.sample(class count 1)
              test_under = pd.concat([class_0_under, class_1], axis=0)
              print("total class of 1 and0:",test_under['Outcome'].value_counts())# plot th
              test_under['Outcome'].value_counts().plot(kind='bar', title='count (target)')
               COCAT CTASS OF T ALIGN. N.A.
               1.0
              Name: Outcome, dtype: int64
   Out[914]: <AxesSubplot:title={'center':'count (target)'}>
                                    count (target)
                200
               175
               150
               125
               100
                75
                50
                25
                 0
```

Models on balanced Dataset with unscaled data

```
In [921]: N X = test_under[[ 'Glucose', 'Pregnancies', 'Age','Insulin', 'BMI']]
y = test_under['Outcome']
In [922]: N from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,ran)
```

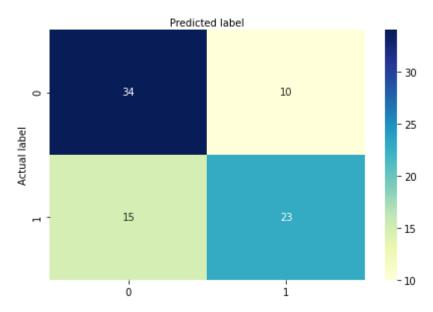
Logistique regression

```
In [923]:  # instantiate the model (using the default parameters)
    classifier8 = LogisticRegression()

# fit the model with data
    classifier8.fit(X_train,y_train)

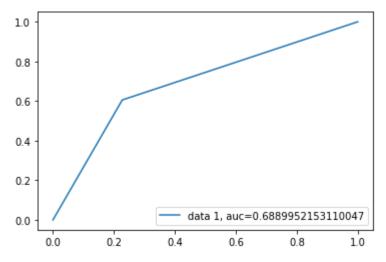
#
y_pred8=classifier8.predict(X_test)
```

Out[924]: Text(0.5, 257.44, 'Predicted label')



```
In [925]:  print("Accuracy:",metrics.accuracy_score(y_test, y_pred8))
  print("Precision:",metrics.precision_score(y_test, y_pred8))
  print("Recall:",metrics.recall_score(y_test, y_pred8))
```

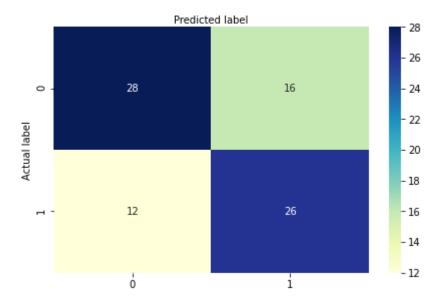
Accuracy: 0.6951219512195121 Precision: 0.6969696969697 Recall: 0.6052631578947368



SVM

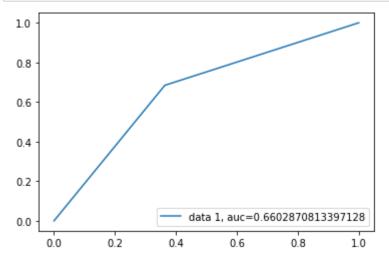
```
In [928]: I
```

Out[928]: Text(0.5, 257.44, 'Predicted label')



```
In [929]:  print("Accuracy:",metrics.accuracy_score(y_test, y_pred9))
  print("Precision:",metrics.precision_score(y_test, y_pred9))
  print("Recall:",metrics.recall_score(y_test, y_pred9))
```

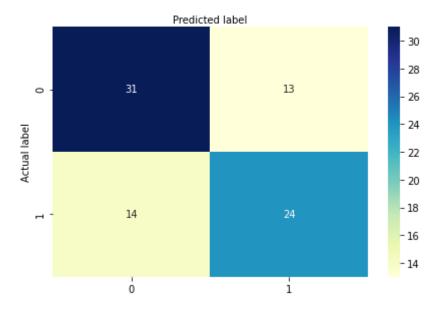
Accuracy: 0.6585365853658537 Precision: 0.6190476190476191 Recall: 0.6842105263157895



Decision tree

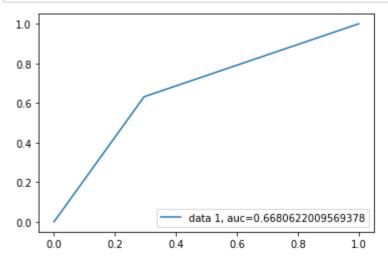
```
In [932]: I
```

Out[932]: Text(0.5, 257.44, 'Predicted label')



```
In [933]: Print("Accuracy:",metrics.accuracy_score(y_test, y_pred10))
print("Precision:",metrics.precision_score(y_test, y_pred10))
print("Recall:",metrics.recall_score(y_test, y_pred10))
```

Accuracy: 0.6707317073170732 Precision: 0.6486486486486487 Recall: 0.631578947368421



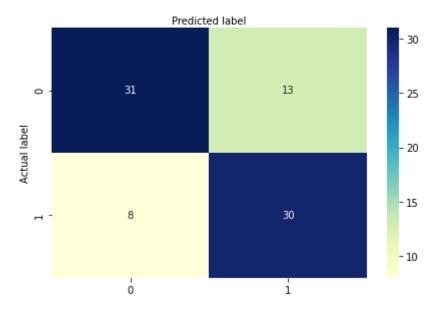
Random Forest

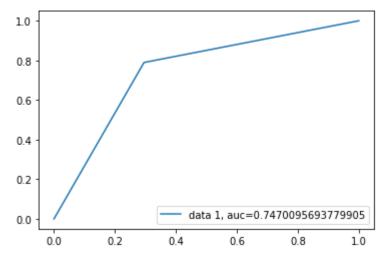
```
In [935]:  #Create a Gaussian Classifier
    classifier11=RandomForestClassifier(n_estimators=100)

#Train the model using the training sets y_pred=clf.predict(X_test)
    classifier11.fit(X_train,y_train)

y_pred11=classifier11.predict(X_test)
```

Out[936]: Text(0.5, 257.44, 'Predicted label')





Undersampling on scaled data

```
X = test_under[[ 'Glucose', 'Pregnancies', 'Age', 'Insulin', 'BMI']]
In [939]:
              y = test under['Outcome']

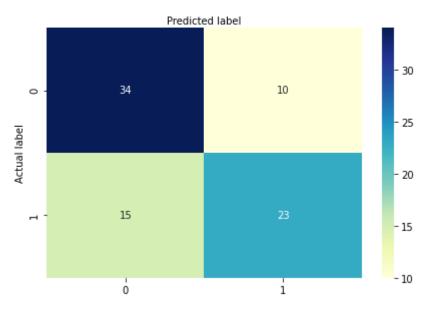
■ Scaler=StandardScaler()
In [940]:
              Scaler.fit(X)
   Out[940]: StandardScaler()
In [941]:
           X= Scaler.transform(X)
              Χ
   Out[941]: array([[-0.52135248, -0.62612848, -0.64709258, -0.37114263, -0.04246523],
                     [-0.55439996, -0.90702147, -0.73385598, -0.43786416, -1.51889436],
                     [-1.54582435, -0.90702147, -1.08090959, -1.54544159, -1.15375597],
                     [ 2.12244589, 0.49744351, 2.73668016, 0.98997662, 0.44967782],
                     [ 1.4614963 , 1.3401225 , 0.74112188, 1.15277716,
                                                                          1.7991023 ],
                     [ 0.00740719, -0.90702147, 1.0881755 , -0.24837501, -0.40760362]])
 In [ ]:
```

Models on balanced Dataset with scaled data

Logistique regression, undersampling and scaled

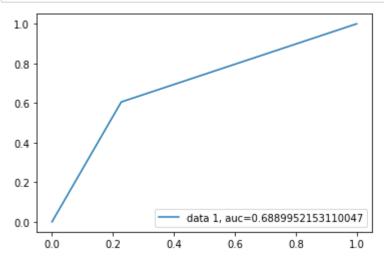
```
In [943]:
          classifier12 = LogisticRegression()
             # fit the model with data
             classifier12.fit(X_train,y_train)
            y_pred12=classifier12.predict(X_test)
In [944]:
          class_names=[0,1] # name of classes
            fig, ax = plt.subplots()
             tick_marks = np.arange(len(class_names))
            plt.xticks(tick_marks, class_names)
            plt.yticks(tick_marks, class_names)
             # create heatmap
             sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
             ax.xaxis.set_label_position("top")
            plt.tight layout()
             plt.title('Confusion matrix', y=1.1)
            plt.ylabel('Actual label')
            plt.xlabel('Predicted label')
```

Out[944]: Text(0.5, 257.44, 'Predicted label')



```
In [945]:  print("Accuracy:",metrics.accuracy_score(y_test, y_pred12))
  print("Precision:",metrics.precision_score(y_test, y_pred12))
  print("Recall:",metrics.recall_score(y_test, y_pred12))
```

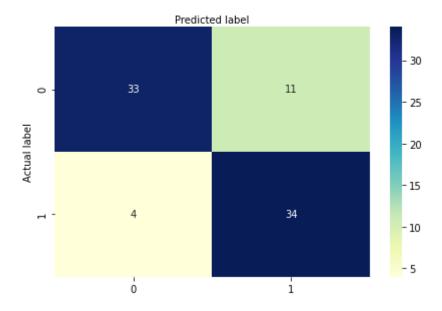
Accuracy: 0.6951219512195121 Precision: 0.696969696969697 Recall: 0.6052631578947368



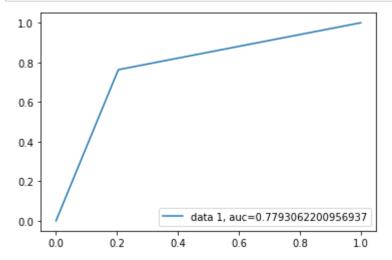
SVM, undersampling and scaled

```
In [948]: I
```

Out[948]: Text(0.5, 257.44, 'Predicted label')

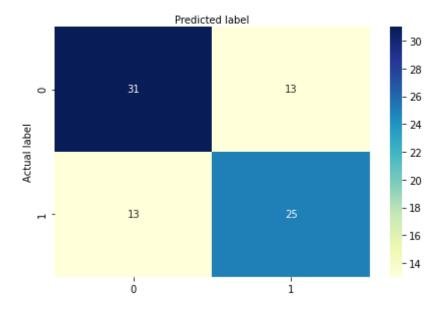


```
In [949]:  print("Accuracy:",metrics.accuracy_score(y_test, y_pred13))
  print("Precision:",metrics.precision_score(y_test, y_pred13))
  print("Recall:",metrics.recall_score(y_test, y_pred13))
```



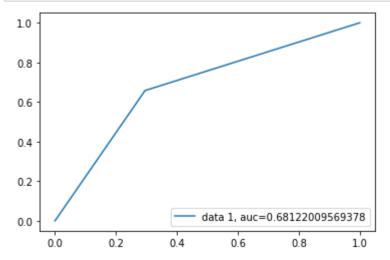
Decision tree

Out[951]: Text(0.5, 257.44, 'Predicted label')



```
In [952]:  print("Accuracy:",metrics.accuracy_score(y_test, y_pred14))
  print("Precision:",metrics.precision_score(y_test, y_pred14))
  print("Recall:",metrics.recall_score(y_test, y_pred14))
```

Accuracy: 0.6829268292682927 Precision: 0.6578947368421053 Recall: 0.6578947368421053



Random Forest

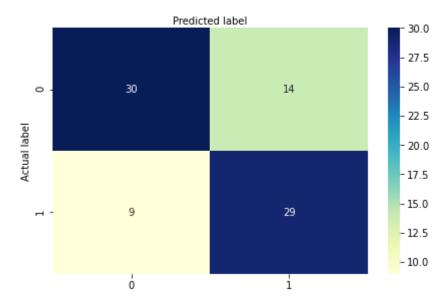
```
In [954]:  #Create a Gaussian Classifier
    classifier15=RandomForestClassifier(n_estimators=100)

#Train the model using the training sets y_pred=clf.predict(X_test)
    classifier15.fit(X_train,y_train)

y_pred15=classifier15.predict(X_test)
```

```
In [955]: I
```

Out[955]: Text(0.5, 257.44, 'Predicted label')



```
In [956]:  print("Accuracy:",metrics.accuracy_score(y_test, y_pred15))
print("Precision:",metrics.precision_score(y_test, y_pred15))
print("Recall:",metrics.recall_score(y_test, y_pred15))
```

Accuracy: 0.7195121951219512 Precision: 0.6744186046511628 Recall: 0.7631578947368421

