Healthcare Diabetes Capstone Project

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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.

Problem Statement:

Build a model to accurately predict whether the patients in the dataset have diabetes or not?

Dataset Description:

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.

- Pregnancies: Number of times pregnant
- Glucose: Plasma glucose concentration a 2 hours in an oral glucose tolerance test
- BloodPressure: Diastolic blood pressure (mm Hg)
- SkinThickness: Triceps skin fold thickness (mm)
- Insulin: 2-Hour serum insulin (mu U/ml)
- BMI: Body mass index (weight in kg/(height in m)^2)
- DiabetesPedigreeFunction: Diabetes pedigree function
- Age: Age (years)
- Outcome: Class variable (0 or 1) 268 of 768 are 1, the others are 0

In [1]:
```
# Import all the tools we need

# Regular EDA (exploratory data analysis) and plotting libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# we want our plots to appear inside the notebook
%matplotlib inline

# Models from Scikit-Learn
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier


# Model Evaluations
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import precision_score,average_precision_score, recall_score, f1_score,  precision_recall_cu
from sklearn.metrics import plot_roc_curve,accuracy_score
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import roc_auc_score
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.tree import plot_tree

#getting rid of the warning notification
import warnings
warnings.filterwarnings("ignore")

np.random.seed(22222134)
```

In [2]:
```
data = pd.read_csv("C:\\Users\\Simeon\\Desktop\\health care diabetes.csv")
```

In [3]:
```
data.head() #checking the top first five rows of data
```

Out[3]:

	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

In [4]:
```
# is there any null or NA values in my data ?
data.isnull().any().sum()

# but what if there are 0 values these will not appear as null or NA so let's check to see
```

Out[4]: 0

In [5]:
```
data.columns
```

Out[5]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

In [6]:
```
data[data['Glucose']==0]
```

Out[6]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
75	1	0	48	20	0	24.7	0.140	22	0
182	1	0	74	20	23	27.7	0.299	21	0
342	1	0	68	35	0	32.0	0.389	22	0
349	5	0	80	32	0	41.0	0.346	37	1
502	6	0	68	41	0	39.0	0.727	41	1

In [7]:
```
(data == 0).astype(int).sum(axis=0)
# we see the amount of zero values in each feature

# we can ignore the Outcome since it is our targte valure and it is normal for it to contain zero's
```

Out[7]:
```
Pregnancies                 111
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
Age                           0
Outcome                     500
dtype: int64
```

In [8]:
```
# checking the percentage of 0 in each features

Glu_percent = round(((5/768)*100),2)
Skin_percent =round(((227/768)*100),2)
BP_percent = round(((35/768)*100),2)
BMI_percent = round(((11/768)*100),2)
Ins_percent = round(((374/768)*100),2)
```

In [9]:
```
percent_info = print(f'your percent missing data for \n Glucose is {Glu_percent}% \n for BloodPressure it is {BP_
\n for BMI is {BMI_percent}% \n for Insulin is {Ins_percent}% and \n for SkinThickness {Skin_percent}% ')
```

```
your percent missing data for
 Glucose is 0.65%
 for BloodPressure it is 4.56%
 for BMI is 1.43%
 for Insulin is 48.7% and
 for SkinThickness 29.56%
```

In [10]:
```
data.columns
```

Out[10]:
```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

In [11]:
```
# I will fill up all the data with their mean to reduce noise but first I
 #need to replace 0 with NaN so I can use the fillna fucntion
from numpy import nan
data_filled = data[['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome']].replace(0,nan)
```

In [12]:
```
(data_filled==0).astype(int).sum(axis=0) #as we can see no more zero values but I expect there to be NAN now
```

Out[12]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [13]:
```
# checking NAN values
data_filled.isna().sum()
```

Out[13]:
```
Pregnancies                 111
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
Age                           0
Outcome                     500
dtype: int64
```

In [14]:
```
# filling the NAN values with their mean
data_filled.describe()
```

Out[14]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	657.000000	763.000000	733.000000	541.000000	394.000000	757.000000	768.000000	768.000000	268.0
mean	4.494673	121.686763	72.405184	29.153420	155.548223	32.457464	0.471876	33.240885	1.0
std	3.217291	30.535641	12.382158	10.476982	118.775855	6.924988	0.331329	11.760232	0.0
min	1.000000	44.000000	24.000000	7.000000	14.000000	18.200000	0.078000	21.000000	1.0
25%	2.000000	99.000000	64.000000	22.000000	76.250000	27.500000	0.243750	24.000000	1.0
50%	4.000000	117.000000	72.000000	29.000000	125.000000	32.300000	0.372500	29.000000	1.0
75%	7.000000	141.000000	80.000000	36.000000	190.000000	36.600000	0.626250	41.000000	1.0
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.0

In [15]:
```
data_filled.fillna(data.mean(),inplace = True)
```

In [16]:
```
data_filled.describe()
```

Out[16]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	4.400782	121.681605	72.254807	26.606479	118.660163	32.450805	0.471876	33.240885	0.576145
std	2.984162	30.436016	12.115932	9.631241	93.080358	6.875374	0.331329	11.760232	0.310515
min	1.000000	44.000000	24.000000	7.000000	14.000000	18.200000	0.078000	21.000000	0.348958
25%	2.000000	99.750000	64.000000	20.536458	79.799479	27.500000	0.243750	24.000000	0.348958
50%	3.845052	117.000000	72.000000	23.000000	79.799479	32.000000	0.372500	29.000000	0.348958
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

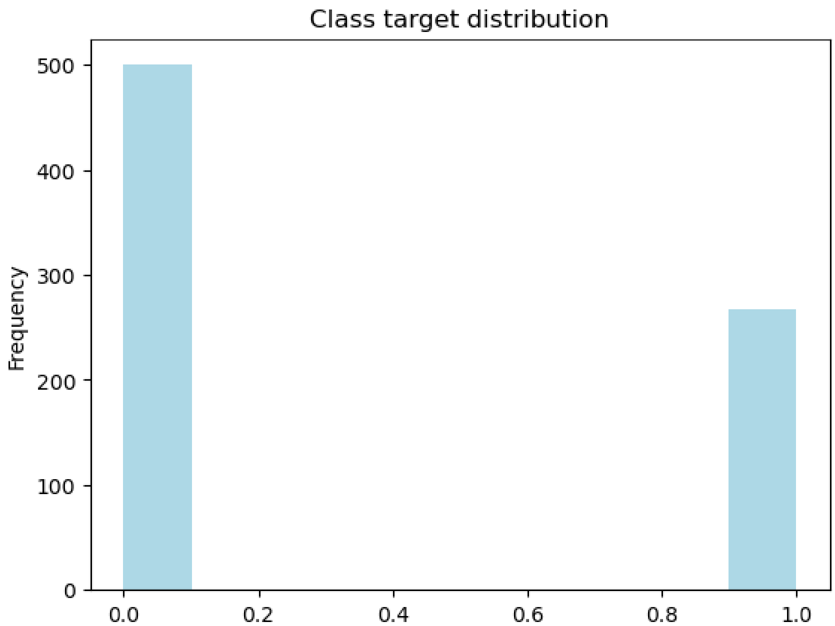
In [17]:
```
# since we see that the dat doesn't have any null values , how about duplicates ?

data_filled.duplicated().sum()
```

Out[17]: 0

In [18]:
```
# next I want to see info about my dataset
data_filled.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    float64
 1   Glucose                   768 non-null    float64
 2   BloodPressure             768 non-null    float64
 3   SkinThickness             768 non-null    float64
 4   Insulin                   768 non-null    float64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    float64
dtypes: float64(8), int64(1)
memory usage: 54.1 KB
```

In [19]:
```
#checking the distribution of the target variable of the data for bias

data['Outcome'].plot(kind = 'hist', color = 'lightblue')
plt.title('Class target distribution');
```

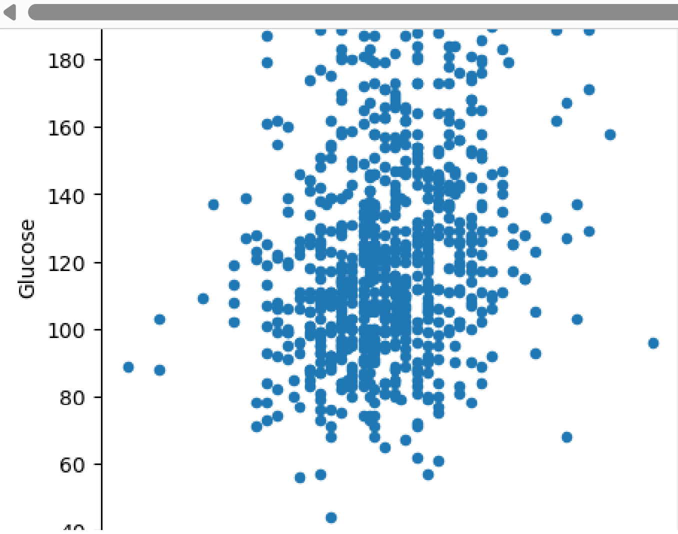


In [20]:
```
data['Outcome'].value_counts()  #we see the exact values of the targetb of the dataset
```

Out[20]:
```
0    500
1    268
Name: Outcome, dtype: int64
```

we can see that the daata is imbalance wich is expected because it is a real life scenario. To solve this I can use the right Evaluation metric or Undersample the abundant class

In [21]:
```
# Create scatter charts between the pair of variables to understand the relationships. Describe your findings.
data_filled.plot(kind = 'scatter', x ='Pregnancies', y = 'Glucose', title = 'Scattterplot of Glucose and Pregnanc
data_filled.plot(kind = 'scatter', x ='BloodPressure', y = 'Glucose', title = 'Scattterplot of Glucose and Blood
data_filled.plot(kind = 'scatter', x = 'BloodPressure', y = 'SkinThickness', title = 'Scattterplot of Blood Pressu
data_filled.plot(kind = 'scatter', x = 'Age', y = 'Insulin', title = 'Scatterplot of Age and Insulin', figsize =

;
# Pregnancies Glucose BloodPressure SkinThickness Insulin BMI
```

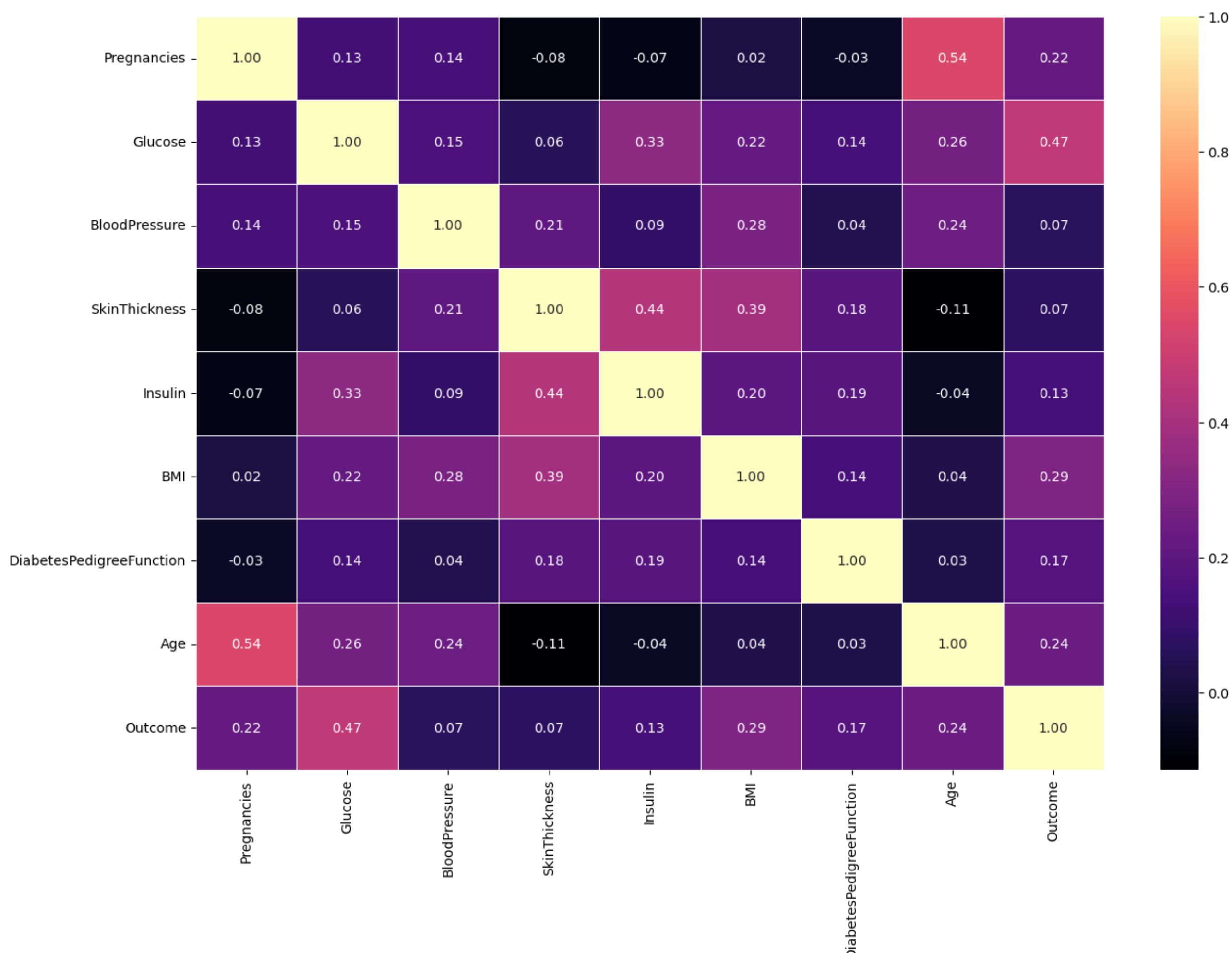


In [22]:
```
### correlation matrix
data.corr()
```

Out[22]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	C
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.017683	-0.033523	0.544341	0
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357	0.221071	0.137337	0.263514	0
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933	0.281805	0.041265	0.239528	0
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.392573	0.183928	-0.113970	0
Insulin	-0.073535	0.331357	0.088933	0.436783	1.000000	0.197859	0.185071	-0.042163	0
BMI	0.017683	0.221071	0.281805	0.392573	0.197859	1.000000	0.140647	0.036242	0
DiabetesPedigreeFunction	-0.033523	0.137337	0.041265	0.183928	0.185071	0.140647	1.000000	0.033561	0
Age	0.544341	0.263514	0.239528	-0.113970	-0.042163	0.036242	0.033561	1.000000	0
Outcome	0.221898	0.466581	0.065068	0.074752	0.130548	0.292695	0.173844	0.238356	1

In [23]:
```
### create correlation heat map to see the correlation

#This will adjust the shape of the heatmap created
plt.figure(figsize=(15, 10))

#create the heatmap
sns.heatmap(data.corr(),annot = True, linewidths=0.5,
                 fmt=".2f",
                 cmap= "magma" );
```



Correlation Analysis

From the scatterplot,corr function and correlation heatmap We see a positive correlation between

> - Age and Pregnancies
> - Age and Glucose
> - BMI and SKin Thickness
> - Insulin and SKin Thickness

and a Negative correlation between

> - Insulin and Pregnancies
> - Age and Insulin
> - Age and SKin Thickness

Data Modeling:

This is a classification problem, so I will be trying different classification models.

- Logistic regression
- Naive Bayes
- Random Forest Classifier
- Decision Tree

I will build the following models and compare them to the KNN model

- K Nearest Neighbour

My approach is to split the data into train and test and apply the following models to train the features.

Then I will check their accuracy scores and also the roc/auc

In [24]:
```
# creating the features and label

# Split data into X and y
X = data_filled.drop("Outcome", axis=1)

y = data["Outcome"]
```

In [25]:
```

#creating Training and testing dataset
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,
                                                 random_state = 10)
```

Logisitic regression model

In [26]:
```
#Create Logistic regression model
logRegModel = LogisticRegression()
```

In [27]:
```
# Fit the model to the training data
logRegModel.fit(X_train,y_train)

# Predict on the test data
y_pred = logRegModel.predict(X_test)
```

In [28]:
```

# print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(logRegModel.score(X_test, y_test))
```

In [29]:
```
# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

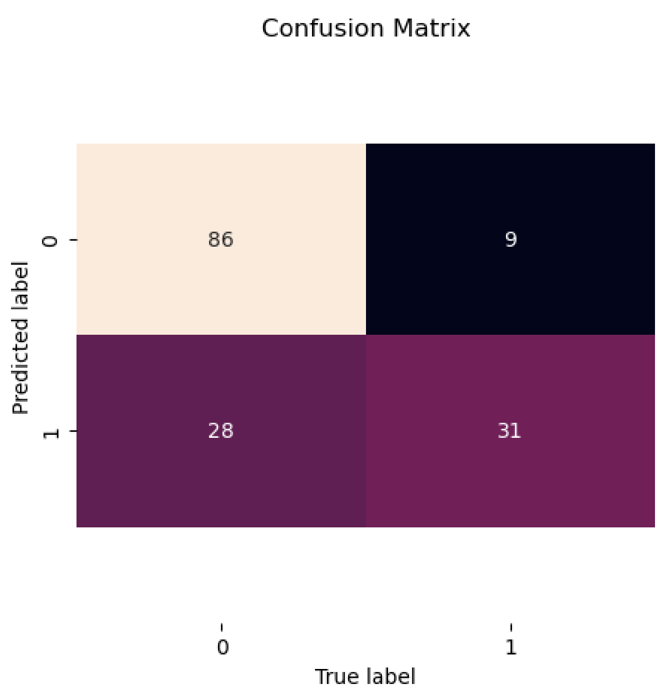
```
Accuracy: 0.7597402597402597
```

In [30]:
```
# using confusin matrix to evalaute performance

confusion_matrix_ = confusion_matrix(y_test, y_pred)
print(confusion_matrix_)
```

```
[[86  9]
 [28 31]]
```

In [31]:
```
 #creating a function to always plot confusion matrix
def plot_conf_mat(y_test, y_pred):
    """
    Plots a confusion matrix using Seaborn's heatmap()
    """
    fig, ax = plt.subplots(figsize=(5,5
                                   ))
    ax = sns.heatmap(confusion_matrix(y_test, y_pred),
                     annot=True,
                     cbar=False)
    plt.xlabel("True label")
    plt.ylabel("Predicted label")
    plt.title("Confusion Matrix")

    bottom, top = ax.get_ylim()
    ax.set_ylim(bottom + 0.5, top - 0.5)
```

In [32]:
```
plot_conf_mat(y_test,y_pred)
```

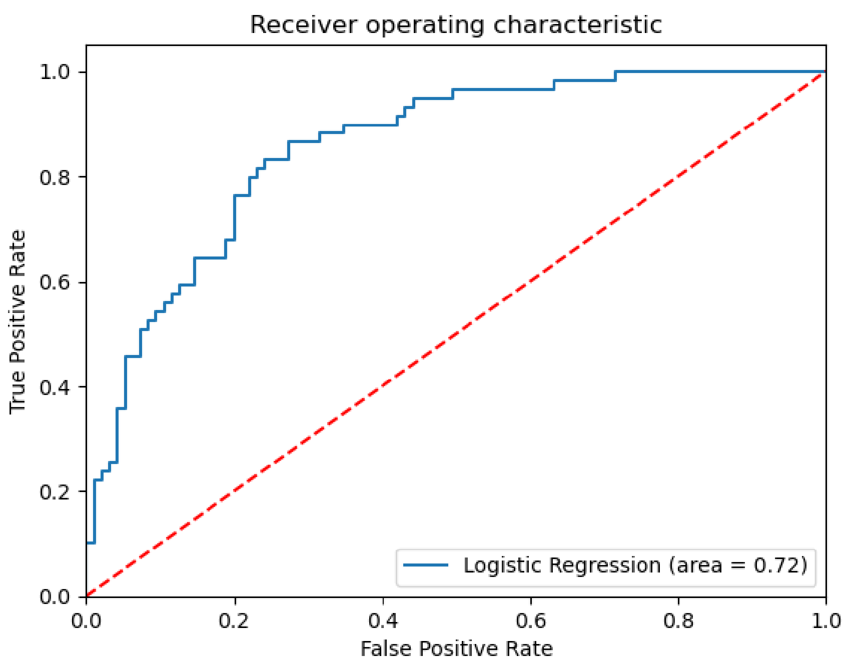


In [33]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.75      0.91      0.82        95
           1       0.78      0.53      0.63        59

    accuracy                           0.76       154
   macro avg       0.76      0.72      0.72       154
weighted avg       0.76      0.76      0.75       154
```

In [34]:
```
logit_roc_auc = roc_auc_score(y_test, logRegModel.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logRegModel.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
print('AUC: %.3f' % logit_roc_auc)
plt.show()
```

```
AUC: 0.715
```



Naive Bayes

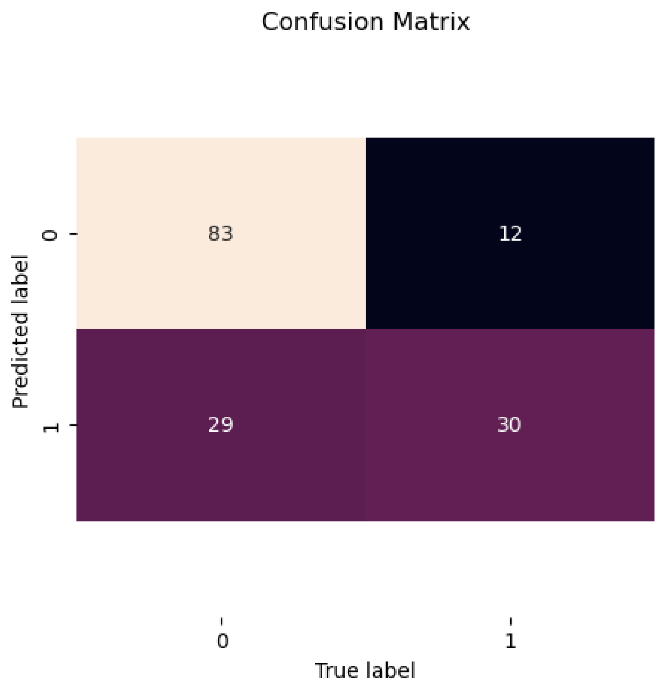
In [35]:
```
# creating the model
nbmodel = GaussianNB()

# training the model
nbmodel.fit(X_train,y_train)

# predicting with the model
y_pred_nb = nbmodel.predict(X_test)

# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred_nb)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.7337662337662337
```

In [36]:
```
# using confusin matrix to evalaute performance

confusion_matrix_ = confusion_matrix(y_test, y_pred_nb)
print(confusion_matrix_)
```

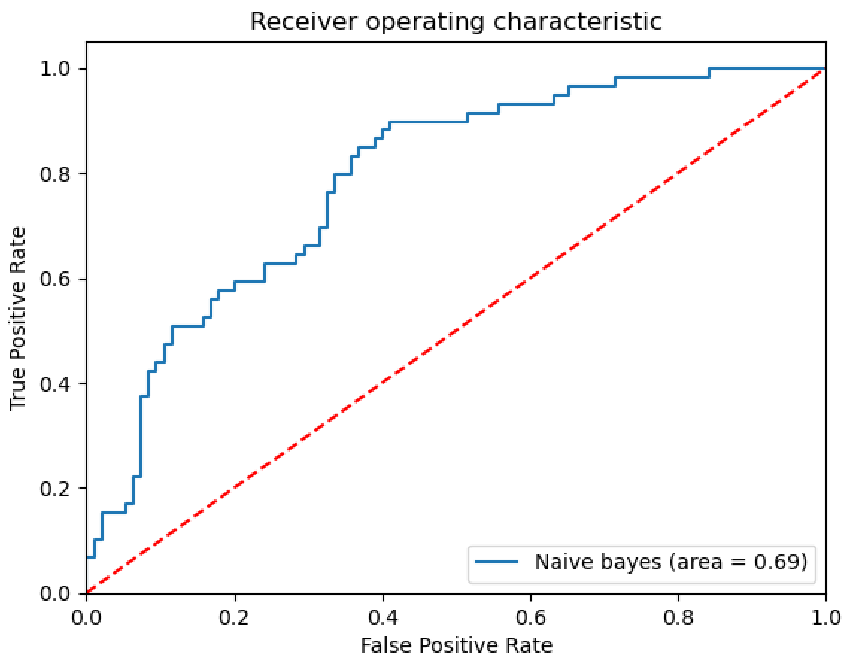
```
[[83 12]
 [29 30]]
```

In [37]:
```
plot_conf_mat(y_test,y_pred_nb)
```



In [38]:
```
# creating AUROC for the model

nb_roc_auc = roc_auc_score(y_test, nbmodel.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, nbmodel.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Naive bayes (area = %0.2f)' % nb_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
print('AUC: %.3f' % nb_roc_auc)
plt.show()
```

```
AUC: 0.691
```



In [39]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.75      0.91      0.82        95
           1       0.78      0.53      0.63        59

    accuracy                           0.76       154
   macro avg       0.76      0.72      0.72       154
weighted avg       0.76      0.76      0.75       154
```

Decision Tree

In [40]:
```
for i in range(3,20):
    print("For max_depth = ",i)
    DTModel = DecisionTreeClassifier(max_depth=i)
    DTModel.fit(X_train,y_train)
    y_pred = DTModel.predict(X_test)
    print("Accuracy:", metrics.accuracy_score(y_test, y_pred))
```

```
For max_depth =  3
Accuracy: 0.6883116883116883
For max_depth =  4
Accuracy: 0.7597402597402597
For max_depth =  5
Accuracy: 0.7467532467532467
For max_depth =  6
Accuracy: 0.7727272727272727
For max_depth =  7
Accuracy: 0.7532467532467533
For max_depth =  8
Accuracy: 0.7597402597402597
For max_depth =  9
Accuracy: 0.7532467532467533
For max_depth =  10
Accuracy: 0.7272727272727273
For max_depth =  11
Accuracy: 0.7532467532467533
For max_depth =  12
Accuracy: 0.7402597402597403
For max_depth =  13
Accuracy: 0.6948051948051948
For max_depth =  14
Accuracy: 0.7142857142857143
For max_depth =  15
Accuracy: 0.7142857142857143
For max_depth =  16
Accuracy: 0.7207792207792207
For max_depth =  17
Accuracy: 0.7077922077922078
For max_depth =  18
Accuracy: 0.7142857142857143
For max_depth =  19
Accuracy: 0.7077922077922078
```

Highest Accuracy of Decision Tree Model can be observed when max_Depth = 8

In [41]:
```
# using the max_depth obtained to predict
DTModel = DecisionTreeClassifier(max_depth=8)
DTModel.fit(X_train,y_train)
y_pred_DT = DTModel.predict(X_test)
```

In [42]:
```
accuracy = accuracy_score(y_test, y_pred_DT)
accuracy
```

Out[42]:
```
0.7597402597402597
```

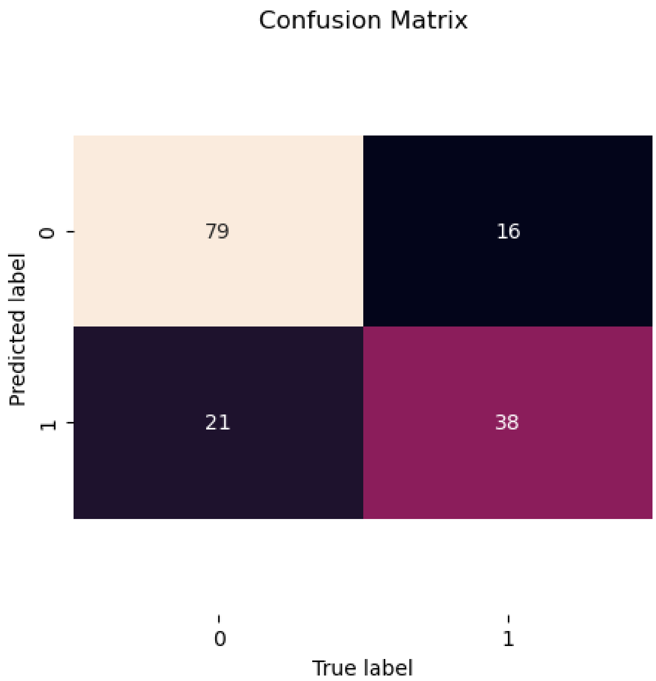
In [43]:
```
print('Accuracy of Decision Tree regression classifier on test set: {:.2f}'.format(DTModel.score(X_test, y_test))
```

```
Accuracy of Decision Tree regression classifier on test set: 0.76
```

In [44]:
```

confusion_matrix_ = confusion_matrix(y_test, y_pred_DT)
print(confusion_matrix_)
```

```
[[79 16]
 [21 38]]
```

In [45]:
```
plot_conf_mat(y_test, y_pred_DT)
```

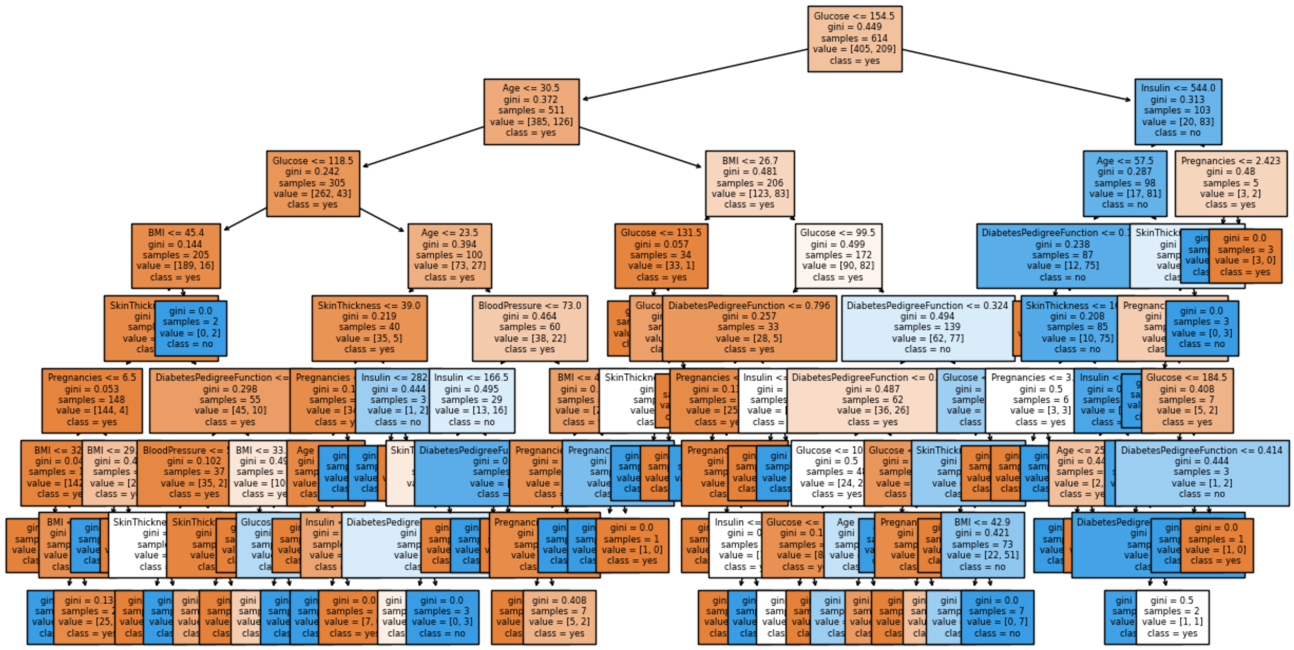


In [46]:
```
# looking at the classification report for the Decision Tree model
print(classification_report(y_test, y_pred_DT))
```

```
              precision    recall  f1-score   support

           0       0.79      0.83      0.81        95
           1       0.70      0.64      0.67        59

    accuracy                           0.76       154
   macro avg       0.75      0.74      0.74       154
weighted avg       0.76      0.76      0.76       154
```

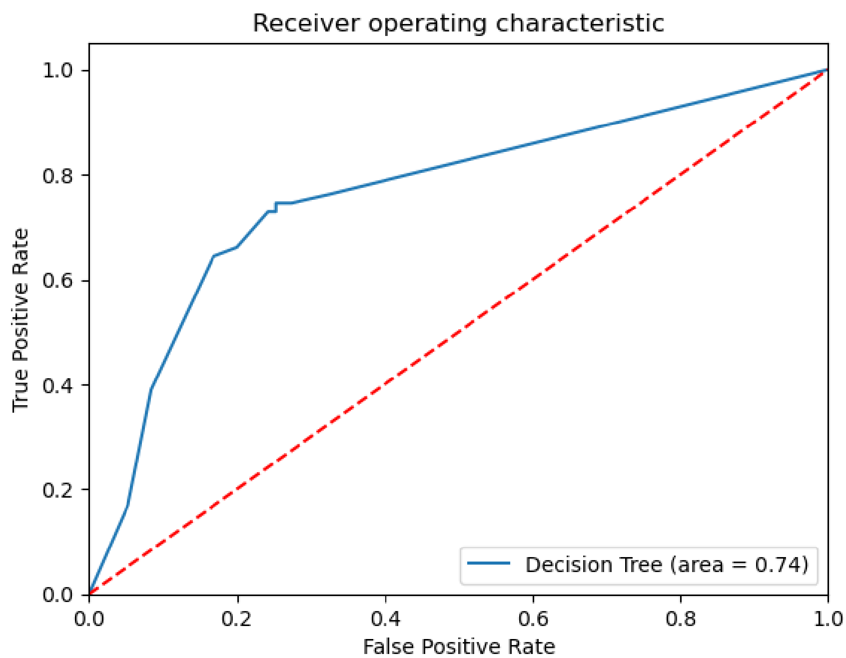
In [47]:
```
# adding features and classs as labels to our decision trees
feature = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age']
class_names = ['yes', 'no']
```

In [48]:
```
# also woul like to plot the tree to see how the decsiion tree was made

plt.figure('Decision tree', figsize =(15,8))
plot_tree(DTModel, fontsize = 6, filled = True,feature_names = feature, class_names = class_names)
plt.show()
```



In [49]:
```
# creating AUROC for the model

dt_roc_auc = roc_auc_score(y_test, DTModel.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, DTModel.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Decision Tree (area = %0.2f)' % dt_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('DT_ROC')
print('AUC: %.3f' % dt_roc_auc)
plt.show()
```

```
AUC: 0.738
```



Random Forest classifier

In [50]:
```
#Building the model
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)
```

In [65]:
```
accuracy = accuracy_score(y_test,y_pred_rf)
accuracy
```

Out[65]:
```
0.7532467532467533
```

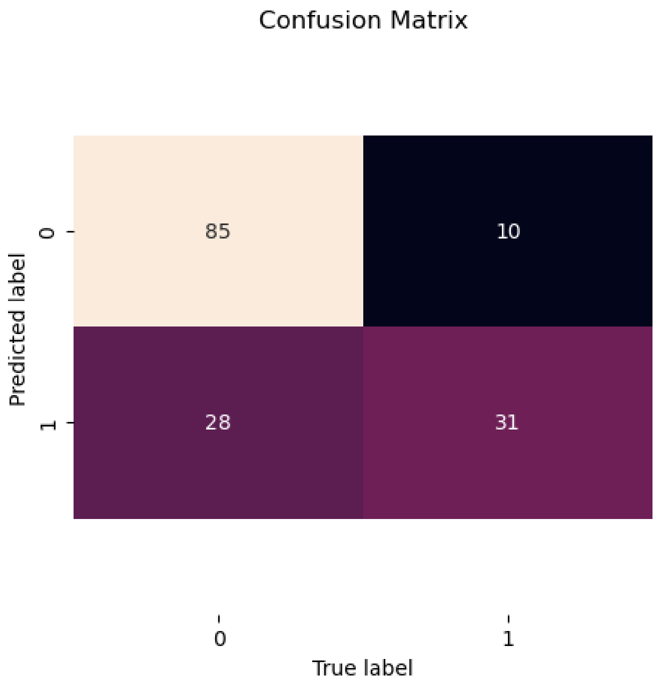
In [51]:
```
print('Accuracy of Random Forest regression classifier on test set: {:.2f}'.format(accuracy_score(y_test,y_pred_r
```

```
Accuracy of Random Forest regression classifier on test set: 0.75
```

In [52]:
```
confusion_matrix_rf = confusion_matrix(y_test, y_pred)
print(confusion_matrix_)
```

```
[[79 16]
 [21 38]]
```

In [53]:
```
plot_conf_mat(y_test,y_pred_rf)
```

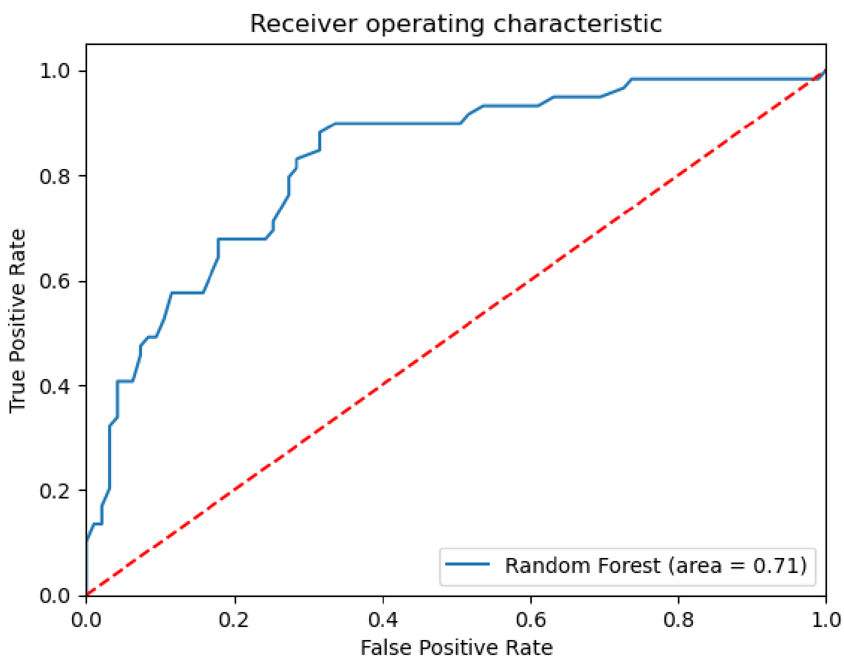


In [54]:
```
print(classification_report(y_test, y_pred_rf))
```

```
              precision    recall  f1-score   support

           0       0.75      0.89      0.82        95
           1       0.76      0.53      0.62        59

    accuracy                           0.75       154
   macro avg       0.75      0.71      0.72       154
weighted avg       0.75      0.75      0.74       154
```

In [55]:
```
rf_roc_auc = roc_auc_score(y_test, rf.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, rf.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Random Forest (area = %0.2f)' % rf_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
print('AUC: %.3f' % rf_roc_auc)
plt.show()
```

```
AUC: 0.710
```



KNN classifier

In [56]:
```
for i in range(3,20):
    print("n_neighbours = ",i)
    KNModel = KNeighborsClassifier(n_neighbors=i)
    KNModel.fit(X_train,y_train)
    y_pred =  KNModel.predict(X_test)
    print("Accuracy:", metrics.accuracy_score(y_test, y_pred))
```

```
n_neighbours =  3
Accuracy: 0.6558441558441559
n_neighbours =  4
Accuracy: 0.6883116883116883
n_neighbours =  5
Accuracy: 0.7142857142857143
n_neighbours =  6
Accuracy: 0.7077922077922078
n_neighbours =  7
Accuracy: 0.7142857142857143
n_neighbours =  8
Accuracy: 0.7077922077922078
n_neighbours =  9
Accuracy: 0.7077922077922078
n_neighbours =  10
Accuracy: 0.7012987012987013
n_neighbours =  11
Accuracy: 0.6753246753246753
n_neighbours =  12
Accuracy: 0.7012987012987013
n_neighbours =  13
Accuracy: 0.6948051948051948
n_neighbours =  14
Accuracy: 0.7012987012987013
n_neighbours =  15
Accuracy: 0.6948051948051948
n_neighbours =  16
Accuracy: 0.6753246753246753
n_neighbours =  17
Accuracy: 0.6883116883116883
n_neighbours =  18
Accuracy: 0.6688311688311688
n_neighbours =  19
Accuracy: 0.6688311688311688
```

In [57]:
```
#Applying K-NN
from sklearn.neighbors import KNeighborsClassifier
knnClassifier = KNeighborsClassifier(n_neighbors=7)
knnClassifier.fit(X_train,y_train)
```

Out[57]:
```
KNeighborsClassifier(n_neighbors=7)
```

In [58]:
```
y_pred_knn = knnClassifier.predict(X_test)
```

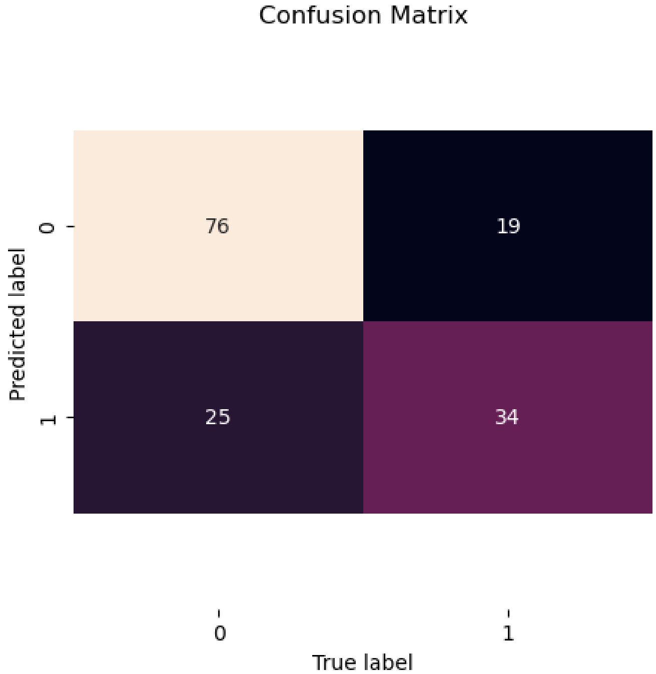
In [59]:
```
accuracy = accuracy_score(y_pred_knn,y_test)
accuracy
```

Out[59]:
```
0.7142857142857143
```

In [60]:
```
confusion_matrix_ = confusion_matrix(y_test, y_pred)
print(confusion_matrix_)
```

```
[[83 12]
 [39 20]]
```

In [61]:
```
plot_conf_mat(y_test,y_pred_knn)
```

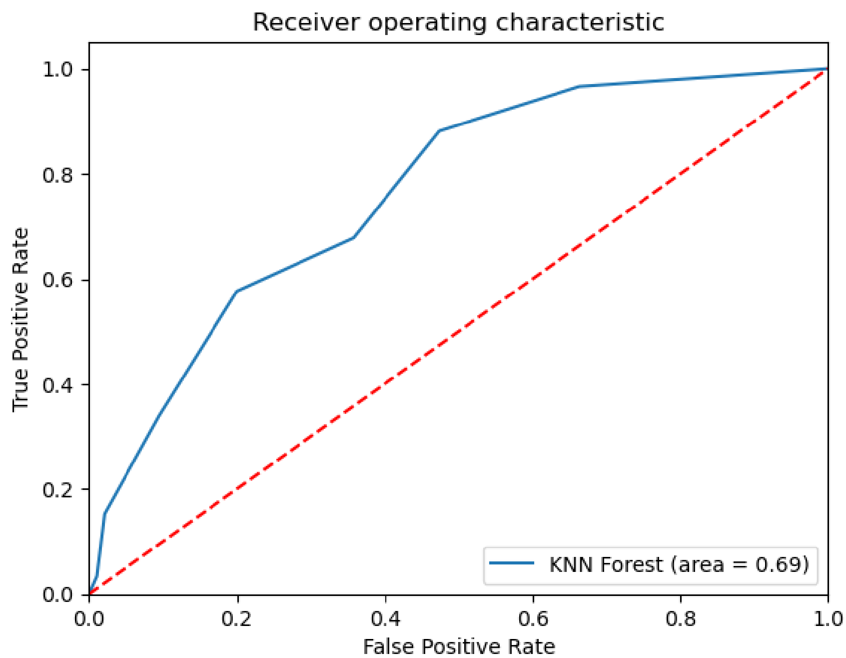


In [62]:
```
print(classification_report(y_test, y_pred_knn))
```

```
              precision    recall  f1-score   support

           0       0.75      0.80      0.78        95
           1       0.64      0.58      0.61        59

    accuracy                           0.71       154
   macro avg       0.70      0.69      0.69       154
weighted avg       0.71      0.71      0.71       154
```

In [63]:
```
knn_roc_auc = roc_auc_score(y_test, knnClassifier.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, knnClassifier.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='KNN Forest (area = %0.2f)' % knn_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
print('AUC: %.3f' % knn_roc_auc)
plt.show()
```

```
AUC: 0.688
```



Conclusion

In conclusion

looking at the model accuracies for all the classification model we see

- Logistic regression has an accuracy of 75.97%
- Naive Bayes has an accuracy of 73.37%
- Random Forest Classifier has an accuracy of 75.32%
- Decision Tree has an accuracy of 75.97%

compared to

- K Nearest Neighbour which has an accuracy of 71.43%

But in terms of AUC Decision tree model has the highest score at 74% which means it has a higher capacity to discriminate True positive class from the negative when compared to the other models.