TOPIC : Heart Failure prediction

In [10]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

In [11]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [12]:
```
data=pd.read_csv('F:\heart_failure_clinical_records_dataset.csv')
data.head()
```

Out[12]:

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	plat
0	75.0	0	582	0	20	1	2650
1	55.0	0	7861	0	38	0	2633
2	65.0	0	146	0	20	0	1620
3	50.0	1	111	0	20	0	2100
4	65.0	1	160	1	20	0	3270

In [13]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 299 entries, 0 to 298
Data columns (total 13 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   age                       299 non-null    float64
 1   anaemia                   299 non-null    int64  
 2   creatinine_phosphokinase  299 non-null    int64  
 3   diabetes                  299 non-null    int64  
 4   ejection_fraction         299 non-null    int64  
 5   high_blood_pressure       299 non-null    int64  
 6   platelets                 299 non-null    float64
 7   serum_creatinine          299 non-null    float64
 8   serum_sodium              299 non-null    int64  
 9   sex                       299 non-null    int64  
 10  smoking                   299 non-null    int64  
 11  time                      299 non-null    int64  
 12  DEATH_EVENT               299 non-null    int64  
dtypes: float64(3), int64(10)
memory usage: 30.5 KB
```

In [14]:
```
data.isnull().sum()
```

Out[14]:
```
age                         0
anaemia                     0
creatinine_phosphokinase    0
diabetes                    0
ejection_fraction           0
high_blood_pressure         0
platelets                   0
serum_creatinine            0
serum_sodium                0
sex                         0
smoking                     0
time                        0
DEATH_EVENT                 0
dtype: int64
```

In [15]:
```
data.describe()
```

Out[15]:

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_
count	299.000000	299.000000	299.000000	299.000000	299.000000	2!
mean	60.833893	0.431438	581.839465	0.418060	38.083612	
std	11.894809	0.496107	970.287881	0.494067	11.834841	
min	40.000000	0.000000	23.000000	0.000000	14.000000	
25%	51.000000	0.000000	116.500000	0.000000	30.000000	
50%	60.000000	0.000000	250.000000	0.000000	38.000000	
75%	70.000000	1.000000	582.000000	1.000000	45.000000	
max	95.000000	1.000000	7861.000000	1.000000	80.000000	

In [16]:
```
data['DEATH_EVENT'].value_counts()
```

Out[16]:
```
0    203
1     96
Name: DEATH_EVENT, dtype: int64
```

In [17]:
```
heart=data.rename(columns = {'DEATH_EVENT':'Target'})
```

In [18]:
```
heart.head()
```

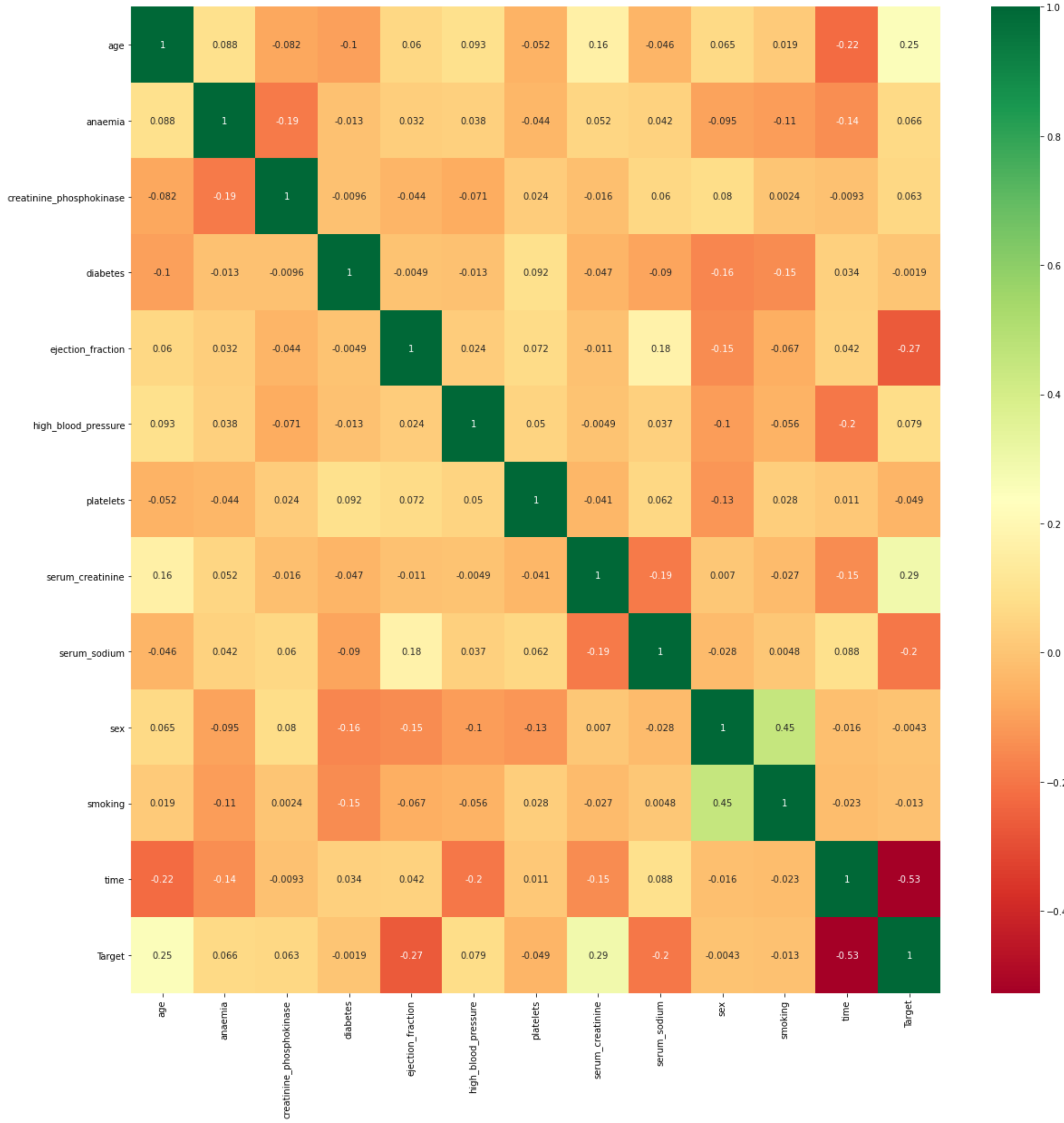
Out[18]:

	age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	plat
0	75.0	0	582	0	20	1	2650
1	55.0	0	7861	0	38	0	2633
2	65.0	0	146	0	20	0	1620
3	50.0	1	111	0	20	0	2100
4	65.0	1	160	1	20	0	3270

In [19]:
```
heart.shape
```

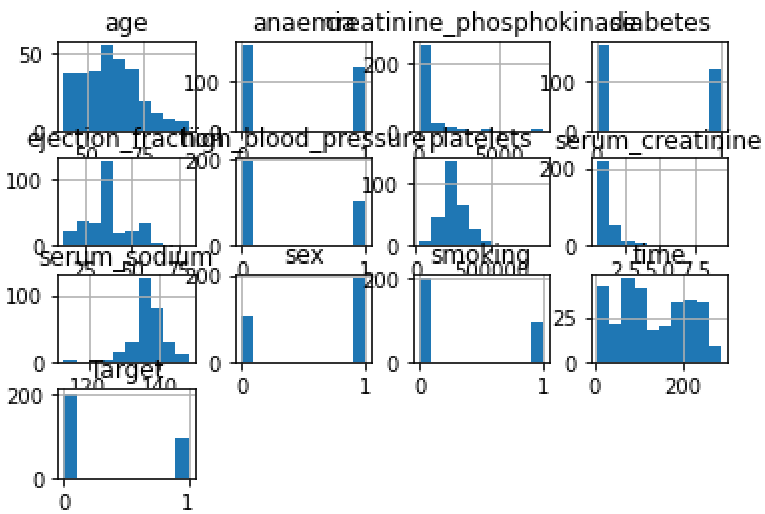
Out[19]:
```
(299, 13)
```

In [20]:
```
import seaborn as sns
corrmat=heart.corr()
top_corr_features=corrmat.index
plt.figure(figsize=(20,20))
g=sns.heatmap(heart[top_corr_features].corr(),annot=True,cmap='RdYlGn')
```



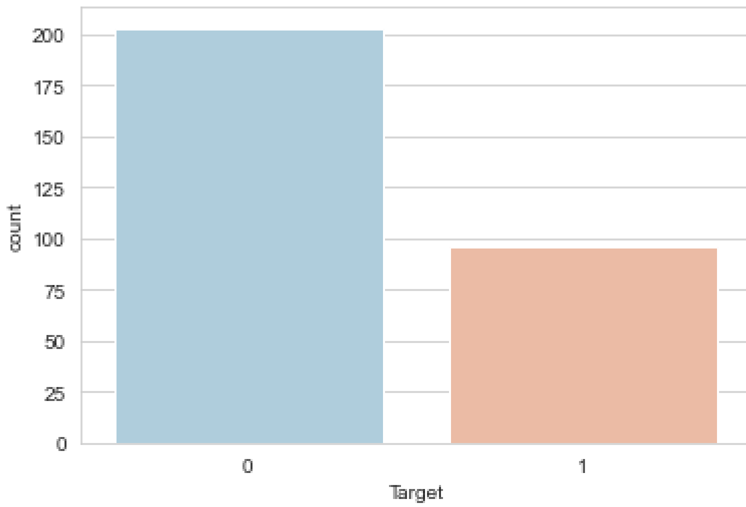
In [21]:
```
heart.hist()
```

Out[21]:
```
array([[<AxesSubplot:title={'center':'age'}>,
        <AxesSubplot:title={'center':'anaemia'}>,
        <AxesSubplot:title={'center':'creatinine_phosphokinase'}>,
        <AxesSubplot:title={'center':'diabetes'}>],
       [<AxesSubplot:title={'center':'ejection_fraction'}>,
        <AxesSubplot:title={'center':'high_blood_pressure'}>,
        <AxesSubplot:title={'center':'platelets'}>,
        <AxesSubplot:title={'center':'serum_creatinine'}>],
       [<AxesSubplot:title={'center':'serum_sodium'}>,
        <AxesSubplot:title={'center':'sex'}>,
        <AxesSubplot:title={'center':'smoking'}>,
        <AxesSubplot:title={'center':'time'}>],
       [<AxesSubplot:title={'center':'Target'}>, <AxesSubplot:>,
        <AxesSubplot:>, <AxesSubplot:>]], dtype=object)
```



In [22]:
```
sns.set_style('whitegrid')
sns.countplot(x='Target',data=heart,palette='RdBu_r')
```

Out[22]: <AxesSubplot:xlabel='Target', ylabel='count'>



data processing

In [23]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
standardscaler = StandardScaler()
```

In [26]:
```
x=heart[['age','ejection_fraction','serum_creatinine','serum_sodium','time']]
y=heart['Target']
```

In [28]:
```
x1=x
y1=y
```

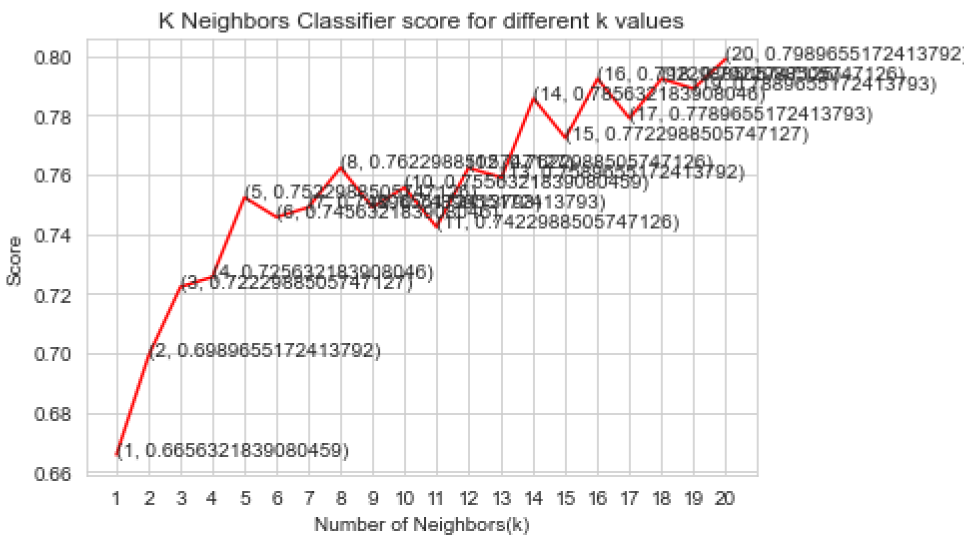
In [29]:
```
x1_train, x1_test, y1_train, y1_test = train_test_split(x1,y1,test_size=0.3,rando
x1_train.shape, x1_test.shape, y1_train.shape, y1_test.shape
```

Out[29]: ((209, 5), (90, 5), (209,), (90,))

In [32]:
```
from sklearn.model_selection import cross_val_score
knn_scores=[]
for k in range(1,21):
 knn_classifier=KNeighborsClassifier(n_neighbors = k)
 score=cross_val_score(knn_classifier,x,y,cv=10)
 knn_scores.append(score.mean())
```

In [33]:
```
plt.plot([k for k in range(1,21)],knn_scores,color='red')
for i in range (1,21):
 plt.text(i,knn_scores[i-1],(i,knn_scores[i-1]))
plt.xticks([i for i in range(1,21)])
plt.xlabel('Number of Neighbors(k)')
plt.ylabel('Score')
plt.title('K Neighbors Classifier score for different k values')
```

Out[33]:
```
Text(0.5, 1.0, 'K Neighbors Classifier score for different k values')
```



In [34]:
```
knn_classifier=KNeighborsClassifier(n_neighbors = 16)
score=cross_val_score(knn_classifier,x,y,cv=10)
```

In [35]:
```
knn_accuracy=score.mean()*100
```

In [36]:
```
knn_accuracy
```

Out[36]:
```
79.22988505747126
```

Logistic Regression

In [37]:
```
from sklearn.linear_model import LogisticRegression
```

In [38]:
```
from sklearn import metrics as sm
```

In [39]:
```
x2=x
y2=y
```

In [40]:
```
x2_train, x2_test, y2_train, y2_test = train_test_split(x2,y2,test_size=0.3,rando
x2_train.shape, x2_test.shape, y2_train.shape, y2_test.shape
```

Out[40]:
```
((209, 5), (90, 5), (209,), (90,))
```

In [41]:
```
logR=LogisticRegression(max_iter = 500).fit(x2_train,y2_train)
logR
```

Out[41]:
```
LogisticRegression(max_iter=500)
```

In [42]:
```
logR.predict_proba(x2_test)
```

Out[42]:
```
array([[9.43089617e-01, 5.69103832e-02],
       [9.93518225e-01, 6.48177490e-03],
       [9.05303317e-01, 9.46966828e-02],
       [1.08528459e-04, 9.99891472e-01],
       [8.71977309e-01, 1.28022691e-01],
       [9.91387698e-01, 8.61230176e-03],
       [3.29755341e-01, 6.70244659e-01],
       [8.47217649e-01, 1.52782351e-01],
       [3.17773583e-02, 9.68222642e-01],
       [8.64932306e-01, 1.35067694e-01],
       [8.74646020e-01, 1.25353980e-01],
       [9.20336061e-01, 7.96639393e-02],
       [8.67200355e-01, 1.32799645e-01],
       [8.00601756e-01, 1.99398244e-01],
       [6.99966378e-01, 3.00033622e-01],
       [6.06936604e-01, 3.93063396e-01],
       [9.54273442e-01, 4.57265576e-02],
       [6.47639285e-01, 3.52360715e-01],
       [8.20348838e-01, 1.79651162e-01],
       [5.42620714e-01, 4.57379286e-01],
       [5.98861869e-01, 4.01138131e-01],
       [7.67116276e-01, 2.32883724e-01],
       [8.05931086e-01, 1.94068914e-01],
       [3.12582051e-01, 6.87417949e-01],
       [4.37509400e-01, 5.62490600e-01],
       [9.96207887e-01, 3.79211271e-03],
       [9.85102190e-01, 1.48978097e-02],
       [9.54122611e-01, 4.58773887e-02],
       [9.32280666e-01, 6.77193344e-02],
       [9.86751896e-01, 1.32481040e-02],
       [1.32568466e-01, 8.67431534e-01],
       [9.88571413e-01, 1.14285872e-02],
       [4.05660604e-01, 5.94339396e-01],
       [6.57575389e-02, 9.34242461e-01],
       [4.04091582e-01, 5.95908418e-01],
       [6.39594493e-01, 3.60405507e-01],
       [8.74625369e-01, 1.25374631e-01],
       [8.83318594e-01, 1.16681406e-01],
       [7.11912032e-01, 2.88087968e-01],
       [9.68948562e-01, 3.10514379e-02],
       [4.38633363e-01, 5.61366637e-01],
       [1.62832809e-01, 8.37167191e-01],
       [9.42735923e-01, 5.72640773e-02],
       [8.96334813e-01, 1.03665187e-01],
       [5.18280795e-01, 4.81719205e-01],
       [9.30304989e-01, 6.96950105e-02],
       [7.53439505e-01, 2.46560495e-01],
       [9.88845448e-01, 1.11545524e-02],
       [9.81280647e-01, 1.87193526e-02],
       [9.83866157e-01, 1.61338425e-02],
       [3.70900649e-01, 6.29099351e-01],
       [9.89689753e-01, 1.03102466e-02],
       [5.37944904e-01, 4.62055096e-01],
       [9.93578477e-01, 6.42152251e-03],
```

```
       [9.83659954e-01, 1.63400455e-02],
       [7.46600361e-01, 2.53399639e-01],
       [9.66803528e-01, 3.31964720e-02],
       [1.33857360e-01, 8.66142640e-01],
       [9.69585555e-01, 3.04144452e-02],
       [1.31666112e-01, 8.68333888e-01],
       [3.28999495e-02, 9.67100050e-01],
       [6.17673837e-01, 3.82326163e-01],
       [8.60624244e-01, 1.39375756e-01],
       [8.39564266e-01, 1.60435734e-01],
       [4.56372539e-02, 9.54362746e-01],
       [2.94969197e-01, 7.05030803e-01],
       [9.97602940e-01, 2.39706000e-03],
       [1.40135379e-01, 8.59864621e-01],
       [8.99873840e-01, 1.00126160e-01],
       [9.92097021e-01, 7.90297950e-03],
       [2.63437024e-01, 7.36562976e-01],
       [2.33112447e-01, 7.66887553e-01],
       [9.87408243e-01, 1.25917567e-02],
       [9.82679513e-01, 1.73204870e-02],
       [7.07602327e-01, 2.92397673e-01],
       [9.70618470e-01, 2.93815300e-02],
       [4.81606673e-01, 5.18393327e-01],
       [3.92979139e-01, 6.07020861e-01],
       [9.99662396e-01, 3.37604067e-04],
       [9.73217763e-01, 2.67822366e-02],
       [8.15612367e-01, 1.84387633e-01],
       [4.50277705e-01, 5.49722295e-01],
       [8.96498521e-01, 1.03501479e-01],
       [8.58711375e-01, 1.41288625e-01],
       [7.23699499e-01, 2.76300501e-01],
       [9.07532204e-01, 9.24677958e-02],
       [2.35028038e-01, 7.64971962e-01],
       [2.24181817e-01, 7.75818183e-01],
       [1.35071377e-02, 9.86492862e-01],
       [7.90359498e-01, 2.09640502e-01]])
```

In [43]:
```
logR.predict_proba(x2_test).shape
```

Out[43]:
```
(90, 2)
```

In [44]:
```
print(logR.intercept_)
```

```
[6.78008279]
```

In [45]:
```
print(logR.coef_)
```

```
[[ 0.05633004 -0.0743512   0.82202255 -0.0530869  -0.02222585]]
```

In [46]:
```
pred=logR.predict(x2_test)
pred
```

Out[46]:
```
array([0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1,
       0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1,
       1, 0], dtype=int64)
```

In [47]:
```
df1 = pd.DataFrame({'actual': y2_test, 'predictions': pred})
df1.head(10)
```

Out[47]:

	actual	predictions
281	0	0
265	0	0
164	1	0
9	1	1
77	0	0
278	0	0
93	1	1
109	0	0
5	1	1
173	0	0

In [48]:
```
ct = pd.crosstab(df1['actual'], df1['predictions'])
ct
```

Out[48]:

predictions	**0**	**1**
actual		
0	49	4
1	15	22

In [49]:
```
from sklearn.metrics import accuracy_score,f1_score,precision_score,recall_score,
from sklearn.metrics import confusion_matrix
```

In [50]:
```
confusion_matrix(y2_test,pred)
```

Out[50]:
```
array([[49,  4],
       [15, 22]], dtype=int64)
```

In [51]:
```
LogR_accuracy=(sm.accuracy_score(y2_test,pred))*100
LogR_accuracy
```

Out[51]: 78.88888888888889

In [52]:
```
table=pd.DataFrame({'knn accuracy':[knn_accuracy], 'Logistic Regression':[LogR_ac
```

In [53]:
```
table
```

Out[53]:

	knn accuracy	Logistic Regression
0	79.229885	78.888889

```
submitted by MAYUR MAROTI CHANDEKAR
```