In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

import warnings
warnings.filterwarnings('ignore')

from matplotlib.pyplot import MultipleLocator
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.model_selection import train_test_split,cross_val_score, GridSearchCV
from sklearn.neighbors import KNeighborsClassifier, KNeighborsRegressor
from sklearn.metrics import classification_report,f1_score,precision_recall_curve,roc_curve, roc_auc_score,confusion_matrix,
from sklearn.neural_network import MLPClassifier
from sklearn import tree
from imblearn.datasets import make_imbalance
from imblearn.under_sampling import NearMiss
from collections import Counter
```

Data Cleaning

In [2]:
```
df = pd.read_csv('Data2015_2016.csv')
```

In [3]:
```
df = df.dropna()
```

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
SEQN                      0
Age                       0
 Body_Mass_Index          0
Gender                    0
Physical_Activity         0
Total_Caffeine            0
Food_Security             0
Count_Meds                0
Section_I                 0
Section_H                 0
Diabetes                  0
Race_and_Ethnicity        0
Total_Sodium_Intake       0
Diastolic_Blood_Pressure  0
Systolic_Blood_Pressure   0
dtype: int64
```

In [5]:
```
data2015_2016 = df.loc[~((df['Diastolic_Blood_Pressure'] == 0) | (df['Systolic_Blood_Pressure'] == 0))]
data2015_2016
```

Out[5]:

	SEQN	Age	Body_Mass_Index	Gender	Physical_Activity	Total_Caffeine	Food_Security	Count_Meds	Section_I	Section_H	Diabetes	Race_and_Eth
0	83732	62	27.8	1	0	360	2	9	0	0	1	
1	83733	53	30.8	1	0	192	2	1	0	0	2	
2	83734	78	28.8	1	8	306	2	7	1	0	1	
3	83735	56	42.4	2	2	248	2	5	0	0	2	
4	83736	42	20.3	2	5	0	2	1	0	0	2	
...	...	...	...	...	...	...	...	...	...	...	...	...
9537	93696	26	33.8	1	0	0	2	1	0	0	2	
9538	93697	80	31.0	2	2	13	2	4	0	0	2	
9541	93700	35	26.0	1	0	0	2	2	0	0	2	
9542	93701	8	18.1	1	0	5	2	1	0	0	2	
9543	93702	24	21.4	2	0	192	2	1	0	0	2	

7087 rows × 15 columns

In [6]:
```
data2015_2016.to_csv("Data2015_2016_clean.csv", index = False)
```

Label the Target Category

In [7]:
```
data2015_2016['Sy_Label'] = pd.cut(x=data2015_2016['Systolic_Blood_Pressure'],
                       bins=[0,140,250],
                       labels=['0', '1'])
```

In [8]:
```
data2015_2016['Da_Label'] = pd.cut(x=data2015_2016['Diastolic_Blood_Pressure'],
                       bins=[0,140,250],
                       labels=['0', '1'])
```

Combine Systolic and Diastolic Pressure¶

In [9]:
```
class_list = []
for sys, dia in zip(data2015_2016["Sy_Label"],data2015_2016["Da_Label"]):
    if int(sys) + int(dia) >0:
        class_list.append(1)
    else:
        class_list.append(0)
```

In [10]:
```
data2015_2016["target"] = class_list
```

Split X and Y

In [11]:
```
X = data2015_2016.drop(["Diastolic_Blood_Pressure","Systolic_Blood_Pressure","Sy_Label","Da_Label","SEQN"], axis=1)
y = data2015_2016["target"].values
le = LabelEncoder()
y = le.fit_transform(y)
```

In [12]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 42)
```

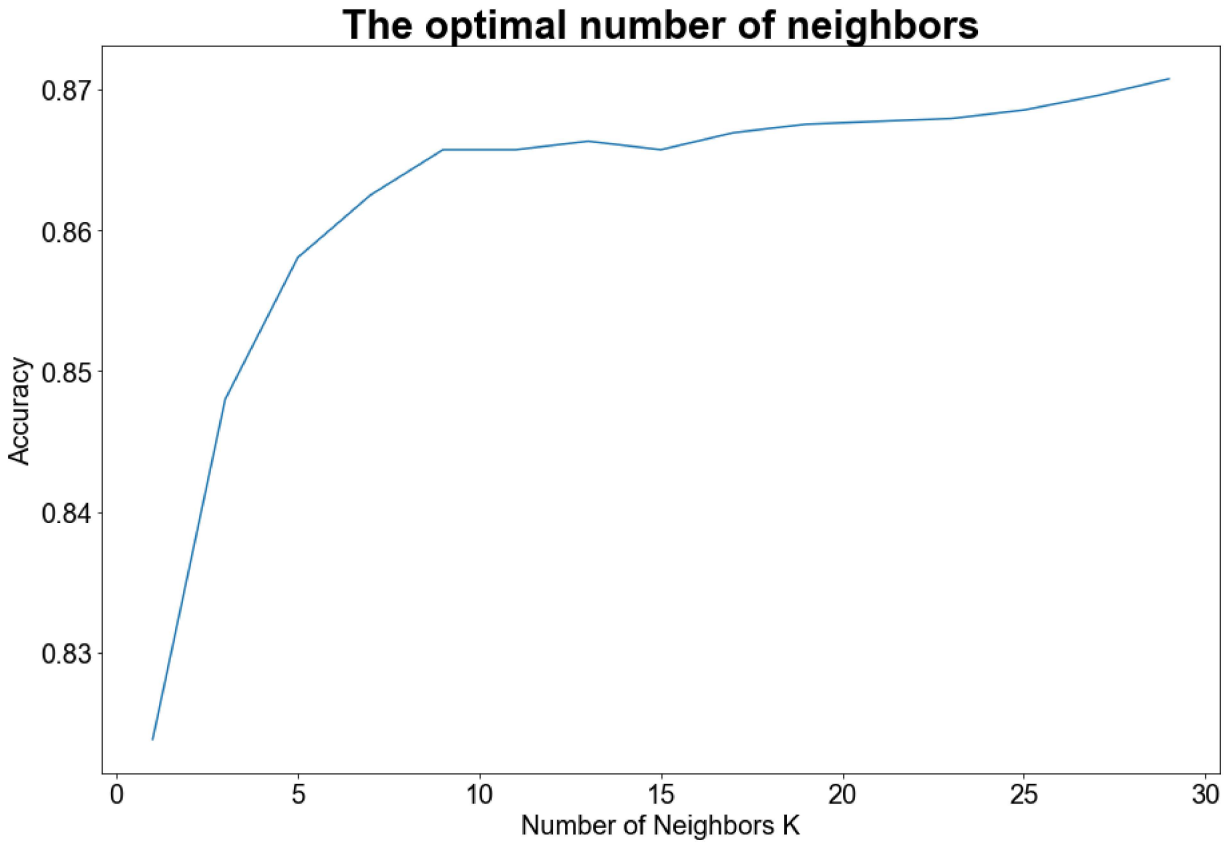
Find the Optimal K_Cross Validation

In [13]:
```
k_list = list(range(1,30,2))

cv_scores = []

for k in k_list:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X_train, y_train, cv=8, scoring='accuracy')
    cv_scores.append(scores.mean())
```

In [14]:

```
plt.figure()
plt.figure(figsize=(15,10))
plt.title('The optimal number of neighbors', fontsize=30, fontweight='bold')
plt.xlabel('Number of Neighbors K', fontsize=20)
plt.ylabel('Accuracy', fontsize=20)
plt.tick_params(axis='both', which='major', labelsize = 20)
sns.set_style("whitegrid")

plt.plot(k_list, cv_scores)
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```

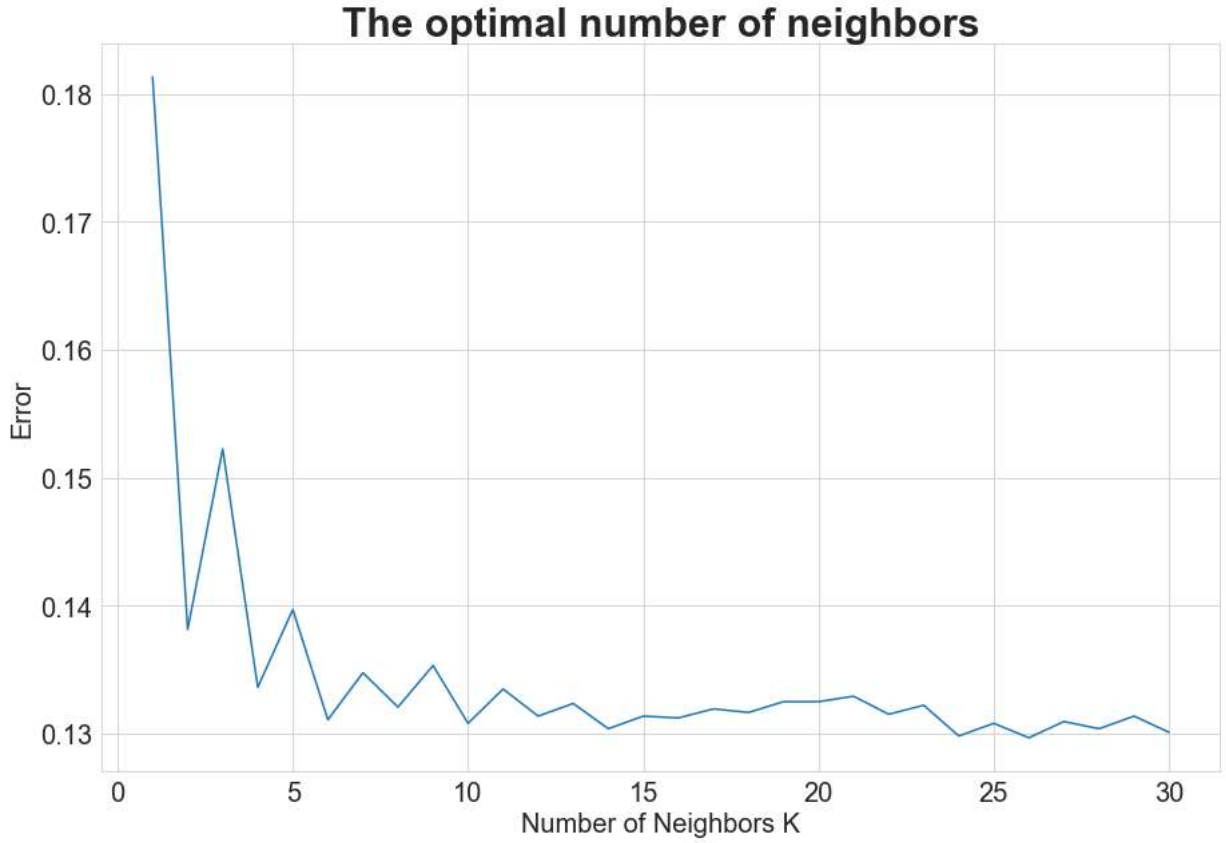


In [15]:

```
# Double Check with whole data

k_range = range(1,31)
k_error = []

for k in k_range:
    KNN = KNeighborsClassifier(n_neighbors = k)
    scores = cross_val_score(KNN, X, y, cv=8, scoring='accuracy')
    a = scores.mean()
    random_state = 42
    print(a)
    k_error.append(1-a)
```

```
0.8186823277346291
0.8618610590350844
0.8477503156444887
0.8663754128884978
0.8603086620499675
0.8689150756909108
0.8652465853005318
0.867927172207981
0.8646812947163025
0.8691980398158421
0.8665168152427594
0.8686332274808382
0.8676454834143169
0.8696211309637678
0.8686338651464718
0.868773992169466
0.8680692122278761
0.8683502633559067
0.8675039216436469
0.8675034433944218
0.8670800334136792
0.8684910280445346
0.8677857698537195
0.870184827383913
0.869196764484575
0.8703255920725408
0.8690556809631302
0.8696206527145427
0.8686327492316129
0.8699031385902489
```

In [16]:
```
plt.figure(figsize=(15,10))
plt.plot(k_range,k_error)
plt.xlabel('Number of Neighbors K', size = 20)
plt.ylabel('Error', size = 20)
plt.title('The optimal number of neighbors',fontsize=30, fontweight='bold')
plt.tick_params(axis='both', which='major', labelsize = 20)
sns.set_style("whitegrid")
plt.show()
```



In this regard,the optimal K will be 5

Define the Confusion Matrxi and Roc Curve Function

In [17]:
```
def plot_cnf_matirx(cnf_matrix,description):
    class_names = [0,1]
    fig,ax = plt.subplots(figsize = (10,8))
    tick_marks = np.arange(len(class_names))
    plt.xticks(tick_marks,class_names)
    plt.yticks(tick_marks,class_names)
    sns.heatmap(pd.DataFrame(cnf_matrix), annot = True, cmap = 'OrRd',
                fmt = 'g',annot_kws={"fontsize":18})
    ax.xaxis.set_label_position('top')

    plt.tight_layout()
    plt.title(description, y = 1.1,fontsize=30)
    plt.ylabel('True',fontsize=20)
    plt.xlabel('Prediction',fontsize=20)
    plt.show()
```

In [18]:
```
def plot_roc_curve(fprs,tprs):
    plt.figure(figsize=(8,6),dpi=80)
    plt.plot(fprs,tprs)
    plt.plot([0,1],linestyle='--')
    plt.xticks(fontsize=17)
    plt.yticks(fontsize=17)
    plt.ylabel('TP rate',fontsize=20)
    plt.xlabel('FP rate',fontsize=20)
    plt.title('ROC Curve for KNN Model',fontsize=25)
    plt.show()
```

KNN model with the optimal K = 5

In [19]:
```
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
```

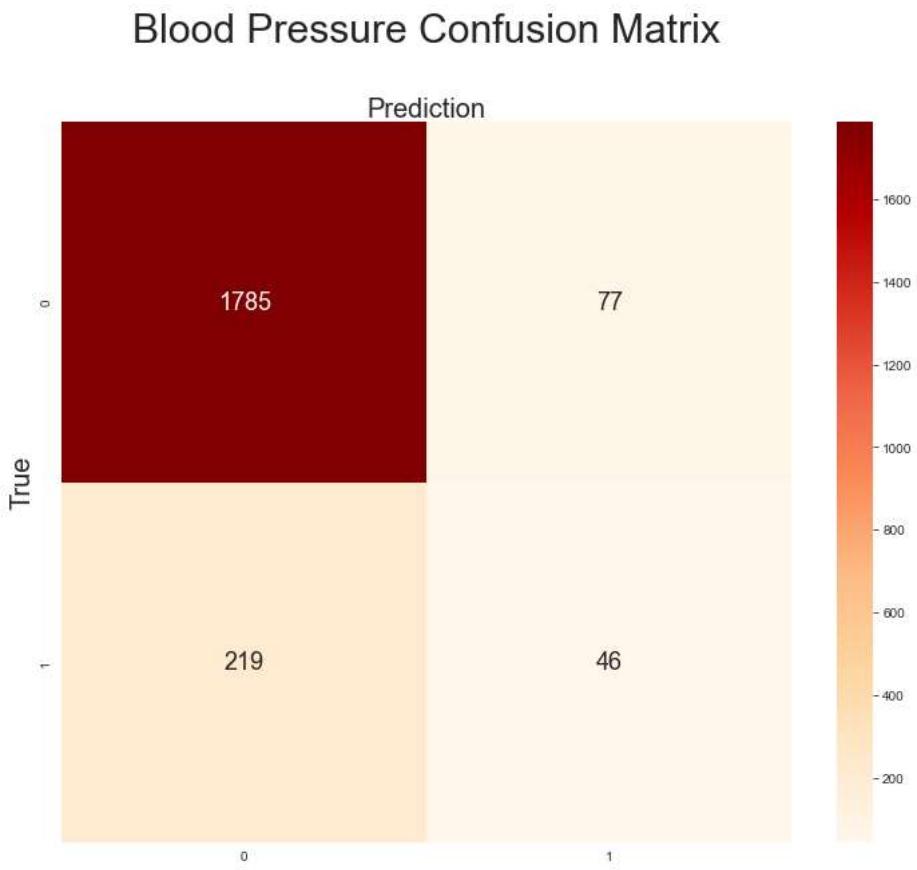
In [20]:
```
accuracy = accuracy_score(y_test, y_pred)*100

print('Accuracy of our model is equal to ' + str(round(accuracy, 2)) + '%')
```

```
Accuracy of our model is equal to 86.08%
```

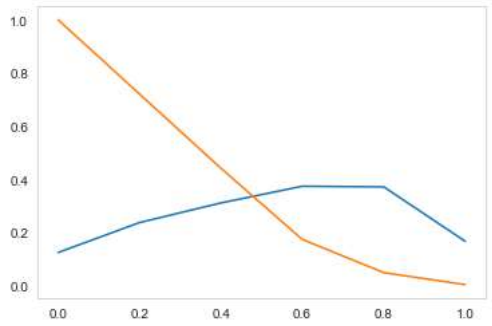
In [21]:
```
Conf_matrix = confusion_matrix(y_test, y_pred)
print(Conf_matrix)
```

```
[[1785   77]
 [ 219   46]]
```

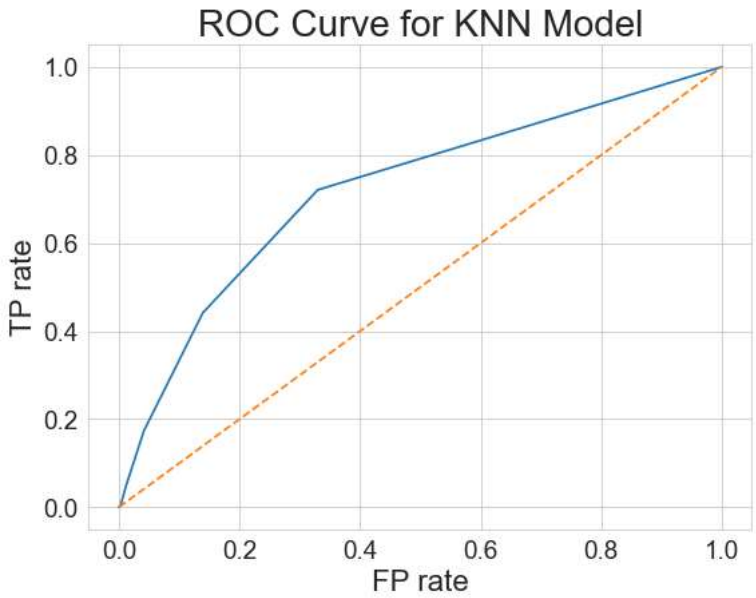
In [22]:
```
plot_cnf_matirx(Conf_matrix,'Blood Pressure Confusion Matrix')
```



In [23]:
```
y_pred = classifier.predict_proba(X_test)[:,1]
precisions,recalls,thresholds = precision_recall_curve(y_test,y_pred)
plt.plot(thresholds,precisions[:-1])
plt.plot(thresholds,recalls[:-1])
plt.grid()
plt.show()
```



In [24]:
```
fprs,tprs,thresholds = roc_curve(y_test,y_pred)
plot_roc_curve(fprs,tprs)
```



In [25]:
```
roc_auc_score(y_test,y_pred)
```

Out[25]: 0.7210566848387816

KNN with the Best Parameter

In [26]:
```
param_grid = [
    {
        'weights':['uniform'],
        'n_neighbors':[5,7,9]
    },
    {
        'weights':['distance'],
        'n_neighbors':[5,7,9],
        'p':[i for i in range(1,6)]
    }
]
```

In [27]:
```
knn_para = KNeighborsClassifier()
grid_search = GridSearchCV(knn_para,param_grid)
grid_search.fit(X_train,y_train)
y_pred_para =grid_search.predict(X_test)
```

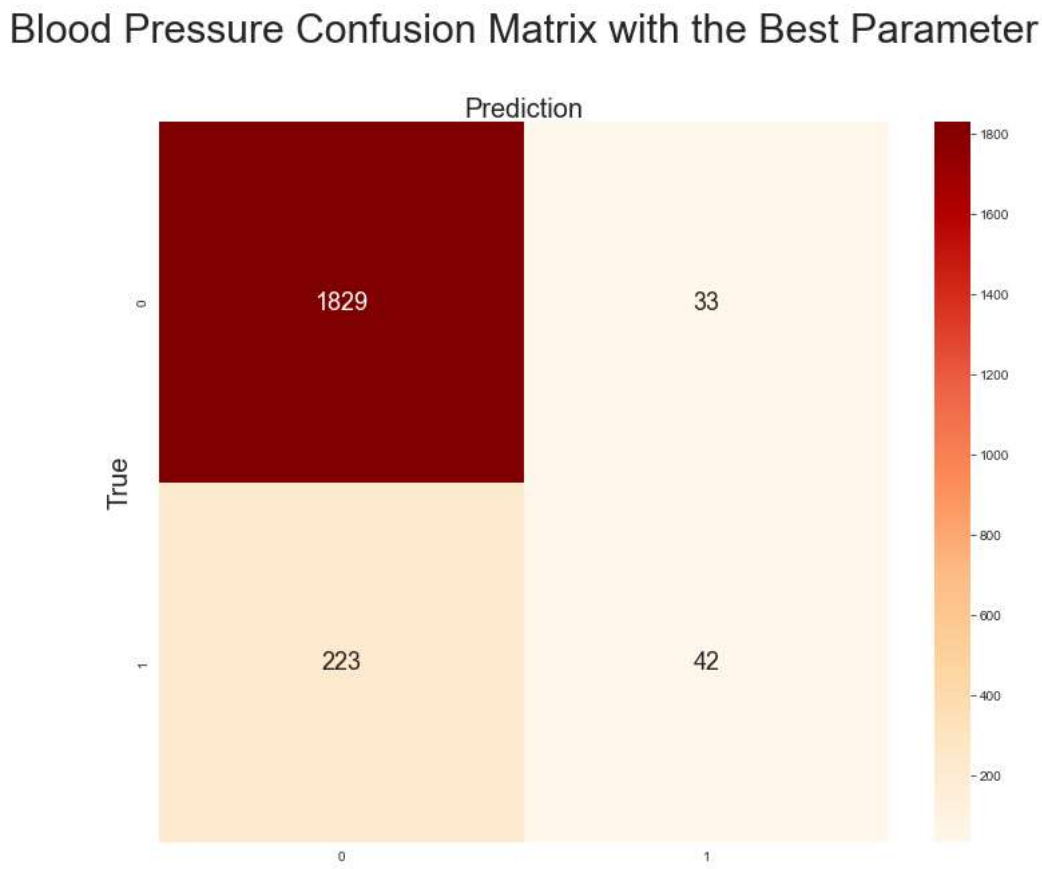
In [28]:
```
accuracy = accuracy_score(y_test, y_pred_para)*100

print('Accuracy of our model is equal to ' + str(round(accuracy, 2)) + '%')
```

```
Accuracy of our model is equal to 87.96%
```

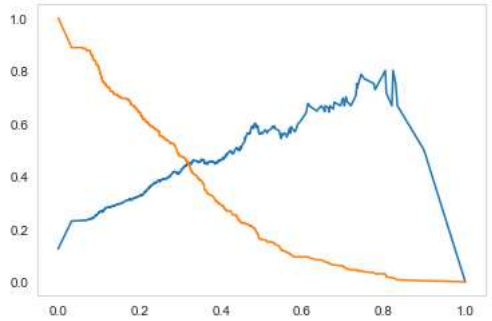
In [29]:
```
Conf_matrix = confusion_matrix(y_test, y_pred_para)
print(Conf_matrix)
```

```
[[1829   33]
 [ 223   42]]
```

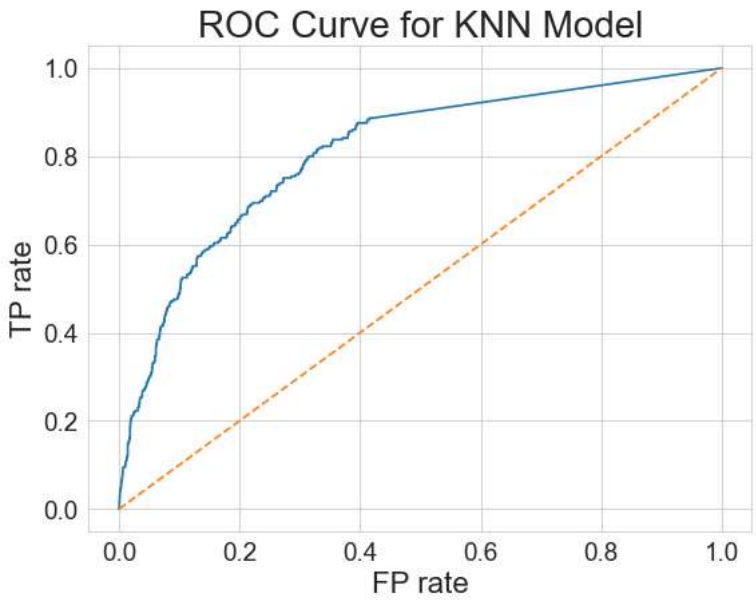
In [30]:
```
plot_cnf_matirx(Conf_matrix,'Blood Pressure Confusion Matrix with the Best Parameter')
```



In [31]:
```
y_pred_para = grid_search.predict_proba(X_test)[:,1]
precisions,recalls,thresholds = precision_recall_curve(y_test,y_pred_para)
plt.plot(thresholds,precisions[:-1])
plt.plot(thresholds,recalls[:-1])
plt.grid()
plt.show()
```



In [32]:
```
fprs,tprs,thresholds = roc_curve(y_test,y_pred_para)
plot_roc_curve(fprs,tprs)
```



In [33]:
```
roc_auc_score(y_test,y_pred_para)
```

Out[33]:
```
0.8078086050706281
```

Imbalanced Data - undersampling

In [34]:
```
data2015_2016.groupby(['target']).size()
```

Out[34]:
```
target
0    6175
1     912
dtype: int64
```

In [35]:
```
undersampling = NearMiss(version = 2, n_neighbors = 5)
X,y = undersampling.fit_resample(X,y)
counter = Counter(y)
print(counter)
```

```
Counter({0: 912, 1: 912})
```

In [36]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 42)
```

Revised KNN with Best Parameter & Resampled data

In [37]:
```
param_grid_imb = [
    {
        'weights':['uniform'],
        'n_neighbors':[5,7,9]
    },
    {
        'weights':['distance'],
        'n_neighbors':[5,7,9],
        'p':[i for i in range(1,6)]
    }
]
```

In [38]:
```
knn_para_imb = KNeighborsClassifier()
grid_search = GridSearchCV(knn_para_imb,param_grid_imb)
grid_search.fit(X_train,y_train)
y_pred_para_imb =grid_search.predict(X_test)
```

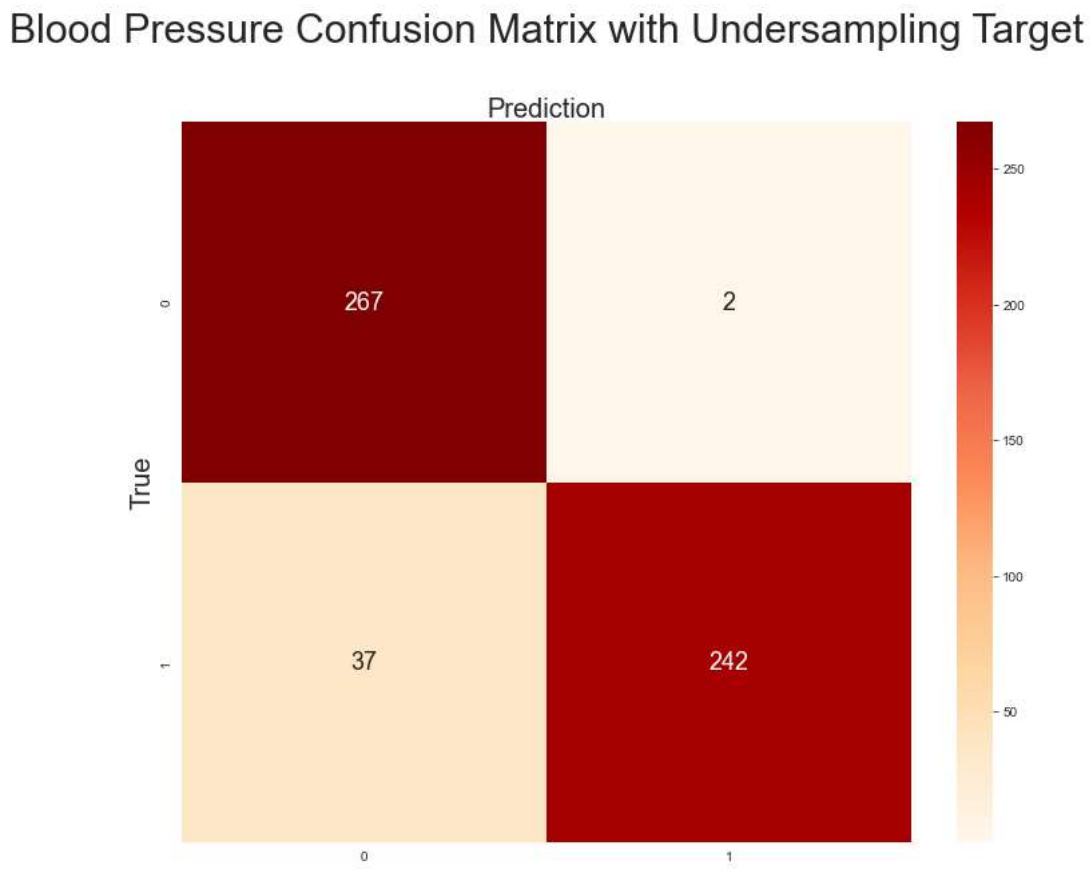
In [39]:
```
accuracy = accuracy_score(y_test, y_pred_para_imb)*100

print('Accuracy of our model is equal to ' + str(round(accuracy, 2)) + '%')
```

```
Accuracy of our model is equal to 92.88%
```

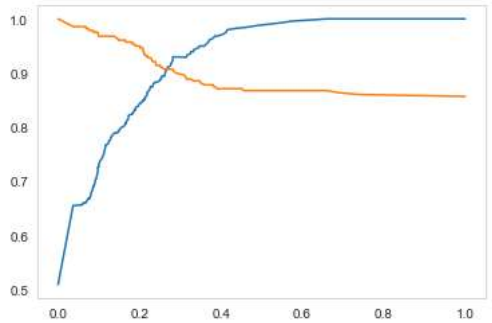
In [40]:
```
Conf_matrix = confusion_matrix(y_test, y_pred_para_imb)
print(Conf_matrix)
```

```
[[267   2]
 [ 37 242]]
```

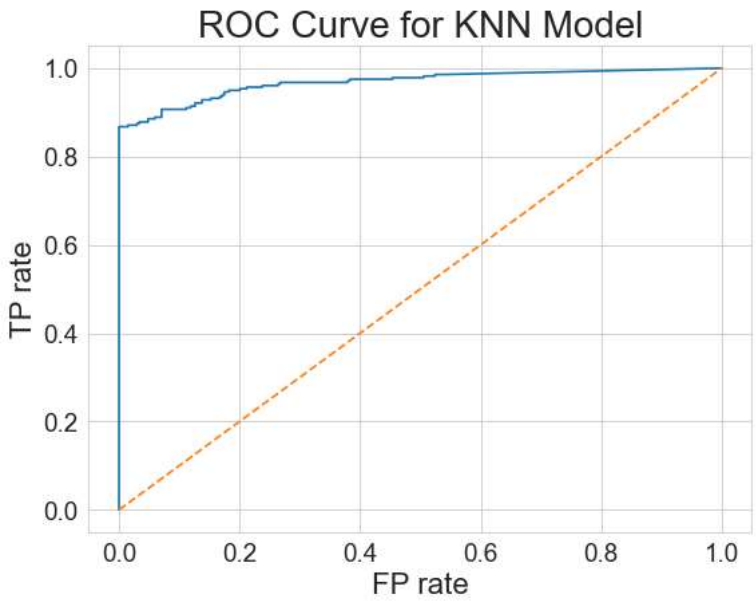
In [41]:
```
plot_cnf_matirx(Conf_matrix,'Blood Pressure Confusion Matrix with Undersampling Target')
```



In [42]:
```
y_pred_para_imb = grid_search.predict_proba(X_test)[:,1]
precisions,recalls,thresholds = precision_recall_curve(y_test,y_pred_para_imb)
plt.plot(thresholds,precisions[:-1])
plt.plot(thresholds,recalls[:-1])
plt.grid()
plt.show()
```



In [43]:
```
fprs,tprs,thresholds = roc_curve(y_test,y_pred_para_imb)
plot_roc_curve(fprs,tprs)
```



In [44]:
```
roc_auc_score(y_test,y_pred_para_imb)
```

Out[44]: 0.9681949607600165