# Problem3

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import random
random.seed(0)
np.random.seed(0)
```

In [2]:
```
columns = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI'
           , 'DiabetesPedigreeFunction', 'Age','Target']
```

In [3]:
```
# Read the data
pima = pd.read_csv('Pima.csv',names=columns)
```

In [4]:
```
pima.head()
```

Out[4]:

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigreeFunction | Age | Target |
|---|---|---|---|---|---|---|---|---|---|
| **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 [5]:
```
# Data information (columns and rows)
pima.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    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Target                    768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

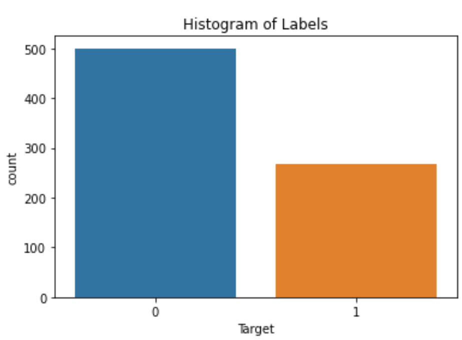
In [6]:
```
# Data Statistics
pima.describe()
```

Out[6]:

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigreeFunction | Age | Target |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 768.000000 | 768.000000 | 768.000000 | 768.000000 | 768.000000 | 768.000000 | 768.000000 | 768.000000 | 768.000000 |
| **mean** | 3.845052 | 120.894531 | 69.105469 | 20.536458 | 79.799479 | 31.992578 | 0.471876 | 33.240885 | 0.348958 |
| **std** | 3.369578 | 31.972618 | 19.355807 | 15.952218 | 115.244002 | 7.884160 | 0.331329 | 11.760232 | 0.476951 |
| **min** | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.078000 | 21.000000 | 0.000000 |
| **25%** | 1.000000 | 99.000000 | 62.000000 | 0.000000 | 0.000000 | 27.300000 | 0.243750 | 24.000000 | 0.000000 |
| **50%** | 3.000000 | 117.000000 | 72.000000 | 23.000000 | 30.500000 | 32.000000 | 0.372500 | 29.000000 | 0.000000 |
| **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 [7]:
```
# Histogram of labels
sns.countplot(x='Target',data=pima)
plt.title("Histogram of Labels")
```

Out[7]: Text(0.5, 1.0, 'Histogram of Labels')




In [8]:
```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix
```

In [9]:
```
X=pima.iloc[:,:8]
y = pima.iloc[:,8:]
accuracy=[]
error=[]
```

In [10]:
```
# 2. Splitting the data (training (80%) and test (20%))
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

In [11]:
```
# K Value Between 1 and 15
for k in range(1,16):
    print("k = ",k)
    knn = KNeighborsClassifier(n_neighbors = k)
    scores = cross_val_score(knn, X_train, y_train.values.ravel(), cv=5, scoring='accuracy') # cv=5 -> no of folds
    print(scores)
    acc = scores.mean()
    print("mean accuracy for k = ",k,"is : ",acc)
    accuracy.append(acc)
    print("*******************")
    error.append(1-acc)
```

```
k =  1
[0.6504065  0.68292683 0.69105691 0.67479675 0.63114754]
mean accuracy for k =  1 is :  0.6660669065707051
*******************
k =  2
[0.65853659 0.69918699 0.72357724 0.69918699 0.69672131]
mean accuracy for k =  2 is :  0.6954418232706917
*******************
k =  3
[0.67479675 0.68292683 0.68292683 0.64227642 0.69672131]
mean accuracy for k =  3 is :  0.6759296281487407
*******************
k =  4
[0.67479675 0.70731707 0.65853659 0.69105691 0.72131148]
mean accuracy for k =  4 is :  0.6906037584966013
*******************
k =  5
[0.70731707 0.69918699 0.67479675 0.69105691 0.7704918 ]
mean accuracy for k =  5 is :  0.7085699053711847
*******************
k =  6
[0.69105691 0.73170732 0.7398374  0.69105691 0.7704918 ]
mean accuracy for k =  6 is :  0.7248300679728109
*******************
k =  7
[0.72357724 0.72357724 0.70731707 0.68292683 0.76229508]
mean accuracy for k =  7 is :  0.7199386911901906
*******************
k =  8
[0.69105691 0.72357724 0.74796748 0.70731707 0.72131148]
mean accuracy for k =  8 is :  0.7182460349193656
*******************
k =  9
[0.72357724 0.71544715 0.69105691 0.71544715 0.7295082 ]
mean accuracy for k =  9 is :  0.7150073304011728
*******************
k =  10
[0.69105691 0.73170732 0.73170732 0.69918699 0.74590164]
mean accuracy for k =  10 is :  0.7199120351859256
*******************
k =  11
[0.69105691 0.73170732 0.75609756 0.69105691 0.75409836]
mean accuracy for k =  11 is :  0.7248034119685458
*******************
k =  12
[0.66666667 0.74796748 0.75609756 0.69105691 0.7295082 ]
mean accuracy for k =  12 is :  0.7182593629214982
*******************
k =  13
[0.68292683 0.72357724 0.7398374  0.69105691 0.73770492]
mean accuracy for k =  13 is :  0.7150206584033054
*******************
k =  14
[0.68292683 0.7398374  0.7398374  0.71544715 0.74590164]
mean accuracy for k =  14 is :  0.7247900839664134
*******************
k =  15
[0.68292683 0.69918699 0.74796748 0.70731707 0.74590164]
mean accuracy for k =  15 is :  0.7166600026656005
*******************
```

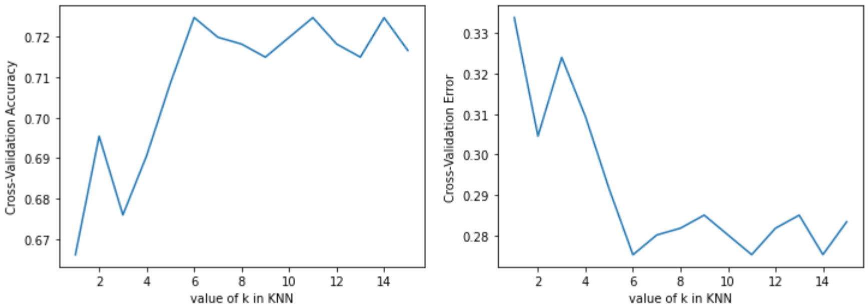
In [12]:
```
print(accuracy) # accuracy for for K=1 to 16
```

```
[0.6660669065707051, 0.6954418232706917, 0.6759296281487407, 0.6906037584966013, 0.7085699053711847, 0.7248300679728109, 0.7199386911901906, 0.7182
460349193656, 0.7150073304011728, 0.7199120351859256, 0.7248034119685458, 0.7182593629214982, 0.7150206584033054, 0.7247900839664134, 0.71666000266
56005]
```

In [13]:
```
# cross validation error for K=1 to 16
print(error)
```

```
[0.3339330934292949, 0.3045581767293083, 0.3240703718512593, 0.30939624150339873, 0.2914300946288153, 0.2751699320271891, 0.2800613088098094, 0.281
75396508063444, 0.2849926695988272, 0.2800879648140744, 0.2751965880314542, 0.28174063707850183, 0.2849793415966946, 0.2752099160335866, 0.28333999
73343995]
```

In [15]:
```python
plt.figure(figsize=(12,4))
k_range = range(1,16)
plt.subplot(1,2,1)
plt.plot(k_range,accuracy)
plt.xlabel('value of k in KNN')
plt.ylabel('Cross-Validation Accuracy')
plt.subplot(1,2,2)
plt.plot(k_range,error)
plt.xlabel('value of k in KNN')
plt.ylabel('Cross-Validation Error')
plt.show()
```




3. Accuracy max for K=6, for all other K values, accuracy is less. So, I will choose K=6

In [16]:
```python
knn = KNeighborsClassifier(n_neighbors=6)
knn.fit(X_train,y_train.values.ravel())
y_pred = knn.predict(X_test)
y_true = y_test.to_numpy().flatten()
total_error=0
total_accuracy=0
for j in range(len(y_pred)):
    if y_pred[j]!=y_true[j]:
        total_error+=1
    else:
        total_accuracy+=1
print("test error ",total_error/len(y_pred))
print("accuracy ",total_accuracy/len(y_pred))
```

```
test error  0.22077922077922077
accuracy  0.7792207792207793
```

In [17]:
```python
X_train_std = (X_train-X_train.mean())/X_train.std()
X_test_std = (X_test-X_test.mean())/X_test.std()
```

In [18]:
```python
knn = KNeighborsClassifier(n_neighbors=6)
knn.fit(X_train_std,y_train.values.ravel())
y_pred_std = knn.predict(X_test_std)
y_true_std = y_test.to_numpy().flatten()
total_error_std=0
total_correct_std=0
for j in range(len(y_pred_std)):
    if y_pred_std[j]!=y_true_std[j]:
        total_error_std+=1
    else:
        total_correct_std+=1
print("test error after standardization ",total_error_std/len(y_pred_std))
print("accuracy after standardization", total_correct_std/len(y_pred_std))
```

```
test error after standardization  0.2012987012987013
accuracy after standardization 0.7987012987012987
```

Yes, centralization and standarization impact the accuracy - because, if the value of different features are very different, then features with larger value will dominate while computing distance, hence will impact the outcome of KNN. Centralization and standardization solve this issue. Therefore, the outcome becomes more reliable.

In [ ]: