CS

September 12, 2023

```
[1]: import sys
     ## import all the packages needed
     import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import sklearn
     import seaborn as sns
[2]: ## read NHANES dataset
     df = pd.read_csv('/Users/zhiyi/Desktop/for Yupei/CS.csv')
[3]: ## find all the distinct values of os
     df.os.value_counts()
[3]: 0
          15392
           4256
     Name: os, dtype: int64
[4]: ## data preparation
     # exclude null values and NA
     df = df[df.os.notnull()]
     # check os
     df.os.describe()
[4]: count
              19648.000000
                  0.216612
    mean
     std
                  0.411947
    min
                  0.000000
    25%
                  0.000000
    50%
                  0.000000
    75%
                  0.000000
    max
                  1.000000
    Name: os, dtype: float64
[5]: # exclude non-numeric values
     d = df.select_dtypes(['number'])
```

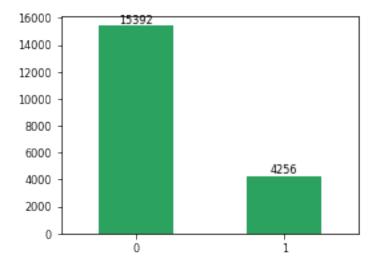
```
# exclude columns that have over 50% NaN
d = d.dropna(thresh = 0.5*len(d), axis =1)
print(len(d.columns), 'columns are left')
```

21 columns are left

```
[6]: ## plot the distribution of values of response variable
vals = d.os.value_counts()

plt.figure(figsize=(4,3))
plt.rc('font', size=8)

ax = vals.plot.bar(rot=0, color='#2ca25f')
for i in range(len(vals)):
    ax.annotate(vals[i], xy=[vals.index[i], vals[i]], ha='center', va='bottom')
```



```
[7]: # replace NA with most frequent values
from sklearn.impute import SimpleImputer
imp_mode = SimpleImputer(strategy='most_frequent')

## show the complete dataset
d = pd.DataFrame(imp_mode.fit_transform(d), columns=d.columns)
d
```

```
[7]:
                 gender
                                                    income
                                                             site grade
                                                                            kind
                                                                                      N
             os
                          race
                                 age
                                      size
                                             marry
              1
                       2
                             2
                                   3
                                         3
                                                          3
                                                                         5
                                                                                  ... 3
                                                                 2
                                                                         2
     1
              0
                       1
                                   3
                                         1
                                                 3
                                                          3
                       2
                                         3
                                                 2
                                                          3
     2
              0
                             1
                                   3
                                                                 2
                                                                         2
                                                                               1 ... 1
                       1
                                   3
                                         1
                                                                         5
```

```
4
                              2
                                                 2
               0
                       1
                                   3
                                          3
                                                          3
                                                                 1
                                                                        2
                                                                               1 ... 1
                       2
      19643
               0
                              1
                                   2
                                          3
                                                 2
                                                          2
                                                                        5
                                                                                     3
                       2
                              2
                                   3
                                          3
                                                          2
                                                                        5
                                                                                     1
      19644
               1
                                                 2
                                                                 1
      19645
               0
                       1
                              1
                                   2
                                          1
                                                 2
                                                          1
                                                                 1
                                                                        5
                                                                                 ... 3
      19646
                       2
                                   2
                                          3
                                                 3
                                                          2
                                                                        5
                                                                                     3
               0
                              1
                                                                 1
                                                                               1
      19647
               1
                       2
                              1
                                   3
                                          3
                                                 3
                                                          2
                                                                 1
                                                                        5
                                                                               1
                                                                                     1
              surgery_pri RX_Summ radiate
                                               chem
                                                      CEA
                                                          bone brain
                                                                        lung
      0
                                  0
                                            0
                                                   0
                                                        1
                                                              0
                                                                      0
                        0
                                                        0
                                                              0
                                                                      0
                                                                             0
      1
                                  0
                                            0
                                                   0
                                                                                    1
                         1
      2
                         0
                                  0
                                            0
                                                   1
                                                        1
                                                              0
                                                                      0
                                                                             0
                                                                                    3
      3
                         0
                                  0
                                            0
                                                   0
                                                        1
                                                              0
                                                                      0
                                                                             1
                                                                                    3
      4
                                            0
                                                        2
                         0
                                  0
                                                   1
                                                              0
                                                                      0
                                                                             1
                                                                                    3
                                                              0
                                                                                    3
      19643
                        0
                                  0
                                            0
                                                   0
                                                        1
                                                                      0
                                                                             1
                                  0
                                                        2
                                                              0
                                                                      0
                                                                             0
                                                                                    3
      19644
                         0
                                            0
                                                   0
      19645
                         0
                                  0
                                                        1
                                                              0
                                                                      0
                                                                             0
                                                                                    3
                                            1
                                                   1
                                                        2
                                  0
                                            0
                                                              0
                                                                             0
                                                                                    3
      19646
                         1
                                                        2
                                                                                    3
      19647
                                            0
                                                              0
                                                                             0
      [19648 rows x 21 columns]
 [8]: ## separate predictors and responses
      X = d.loc[:, d.columns != 'os']
      y = d.os
      print('X shape:', X.shape)
      print('y shape:', y.shape)
     X shape: (19648, 20)
     y shape: (19648,)
 [9]: 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=12)
[10]: from xgboost import XGBClassifier
      from sklearn.metrics import classification_report, accuracy_score, u
       ⇔confusion_matrix
      model = XGBClassifier()
      model.fit(X_train, y_train)
      y_pred = model.predict(X_test)
      accuracy = accuracy_score(y_test, y_pred)
      print("Accuracy: %.2f%%" % (accuracy * 100.0))
```

```
def confusion(y_test, y_pred):
         conf = pd.DataFrame(confusion_matrix(y_test, y_pred), index=['True[0]',__

¬'True[1]'], columns=['Predict[0]', 'Predict[1]'])
         print('Confusion Matrix:')
         print(conf)
         return conf
     confusion(y_test, y_pred)
     Accuracy: 80.33%
     Confusion Matrix:
             Predict[0] Predict[1]
     True[0]
                   2792
                                264
     True[1]
                    509
                                365
[10]:
             Predict[0] Predict[1]
     True[0]
                    2792
     True[1]
                     509
                                 365
[11]: from imblearn.over_sampling import SMOTE
     smote = SMOTE(random_state=12)
     X_train_sm, y_train_sm = smote.fit_resample(X_train, y_train)
     X_test_sm, y_test_sm = smote.fit_resample(X_test, y_test)
     X_train_sm = pd.DataFrame(X_train_sm, columns=X.columns)
     X_test_sm = pd.DataFrame(X_test_sm, columns=X.columns)
     print(y_train_sm.value_counts())
     print(y_test_sm.value_counts())
         12336
     1
     0
          12336
     Name: os, dtype: int64
         3056
     1
          3056
     Name: os, dtype: int64
[12]: # After oversampling, the classification result is more reasonable.
     model = XGBClassifier()
     model.fit(X_train_sm, y_train_sm)
     y_pred_sm = model.predict(X_test_sm)
     accuracy = accuracy_score(y_test_sm, y_pred_sm)
     print("Accuracy: %.2f%%" % (accuracy * 100.0))
     conf = pd.DataFrame(confusion_matrix(y_test_sm, y_pred_sm), index=['True[0]',__
```

```
conf
     Accuracy: 76.62%
[12]:
               Predict[0] Predict[1]
      True[0]
                      2422
                                   634
      True[1]
                       795
                                  2261
[13]: X_scale = d.loc[:, d.columns != 'os']
[14]: ## min-max scaling
      from sklearn.preprocessing import MinMaxScaler
      minmax = MinMaxScaler()
      X = pd.DataFrame(minmax.fit_transform(X_scale), columns=X_scale.columns)
      Х
[14]:
             gender race
                                 size
                                       marry
                                               income
                                                       site
                                                              grade
                                                                     kind
                                                                             Τ
                                                                                   N \
                            age
                                          0.0
      0
                1.0
                       0.5
                            1.0
                                  1.0
                                                  1.0
                                                        0.0
                                                               1.00
                                                                      0.0
                                                                           1.0
                                                                                1.0
      1
                0.0
                                  0.0
                                          1.0
                                                  1.0
                                                               0.25
                                                                      0.0 0.5
                       0.0
                            1.0
                                                        1.0
                                                                                0.5
      2
                1.0
                       0.0
                            1.0
                                  1.0
                                          0.5
                                                  1.0
                                                        1.0
                                                               0.25
                                                                      0.0 0.5 0.0
      3
                0.0
                       1.0
                                  0.0
                                          1.0
                                                  1.0
                                                        0.0
                                                               1.00
                                                                      0.0 0.5 0.0
                            1.0
      4
                0.0
                                          0.5
                                                               0.25
                                                                      0.0 0.0 0.0
                       0.5 1.0
                                  1.0
                                                  1.0
                                                        0.0
                                                   •••
                       0.0
                           0.5
                                  1.0
                                          0.5
                                                  0.5
                                                               1.00
                                                                      0.0
                                                                          0.0
                                                                                1.0
      19643
                1.0
                                                        0.0
                                                                      0.0 0.0 0.0
      19644
                1.0
                       0.5
                            1.0
                                  1.0
                                          0.5
                                                  0.5
                                                        0.0
                                                               1.00
                0.0
                       0.0
                                  0.0
                                          0.5
                                                               1.00
                                                                      0.0
                                                                           1.0 1.0
      19645
                            0.5
                                                  0.0
                                                        0.0
      19646
                1.0
                       0.0
                            0.5
                                  1.0
                                          1.0
                                                  0.5
                                                        0.0
                                                               1.00
                                                                      0.0 1.0 1.0
      19647
                1.0
                       0.0 1.0
                                  1.0
                                          1.0
                                                  0.5
                                                        0.0
                                                               1.00
                                                                      0.0 1.0 0.0
             surgery_pri RX_Summ radiate
                                                    CEA
                                                         bone
                                                               brain
                                                                      lung group
                                              chem
                                                                        0.5
      0
                      0.0
                               0.0
                                         0.0
                                               0.0
                                                    0.5
                                                          0.0
                                                                  0.0
                                                                                1.0
      1
                      1.0
                               0.0
                                         0.0
                                               0.0
                                                    0.0
                                                          0.0
                                                                  0.0
                                                                        0.0
                                                                               0.0
      2
                      0.0
                               0.0
                                         0.0
                                               1.0
                                                    0.5
                                                          0.0
                                                                  0.0
                                                                        0.0
                                                                                1.0
      3
                               0.0
                                         0.0
                                                          0.0
                      0.0
                                               0.0 0.5
                                                                  0.0
                                                                        0.5
                                                                                1.0
      4
                      0.0
                               0.0
                                         0.0
                                               1.0 1.0
                                                          0.0
                                                                  0.0
                                                                        0.5
                                                                                1.0
                      0.0
                                                                  0.0
                                                                        0.5
                                                                               1.0
      19643
                               0.0
                                        0.0
                                               0.0 0.5
                                                          0.0
      19644
                      0.0
                               0.0
                                        0.0
                                               0.0 1.0
                                                          0.0
                                                                  0.0
                                                                        0.0
                                                                               1.0
                      0.0
                               0.0
                                         1.0
                                               1.0 0.5
                                                          0.0
                                                                  0.0
                                                                        0.0
                                                                                1.0
      19645
      19646
                      1.0
                               0.0
                                         0.0
                                               0.0 1.0
                                                           0.0
                                                                  0.0
                                                                        0.0
                                                                                1.0
      19647
                      0.0
                               0.0
                                        0.0
                                               0.0 1.0
                                                          0.0
                                                                  0.0
                                                                        0.0
                                                                                1.0
      [19648 rows x 20 columns]
```

[15]: 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=12)
[16]: from imblearn.over sampling import SMOTE
      smote = SMOTE(random_state=12)
      X_train_sm, y_train_sm = smote.fit_resample(X_train, y_train)
      \#X\_test\_sm, y\_test\_sm = smote.fit\_sample(X\_test, y\_test)
      X_train_sm = pd.DataFrame(X_train_sm, columns=X.columns)
      #X_test_sm = pd.DataFrame(X_test_sm, columns=X.columns)
[17]: print('X train shape: ',X_train_sm.shape)
      print('y train values: \n', y_train_sm.value_counts())
      print()
      print('X test shape: ',X_test_sm.shape)
      print('y test values: \n', y_test_sm.value_counts())
     X train shape: (24672, 20)
     y train values:
           12336
      1
          12336
     Name: os, dtype: int64
     X test shape: (6112, 20)
     y test values:
      0
           3056
          3056
     Name: os, dtype: int64
[18]: mscore=[]
[19]: from sklearn.linear_model import LogisticRegression
      from time import process_time
      clf = LogisticRegression(max_iter=100, solver='lbfgs', class_weight='balanced',__
       →random_state=12)
      start = process_time()
      clf.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      clf_prediction_proba = clf.predict_proba(X_test)[:, 1]
      y_pred = clf.predict(X_test)
```

```
print('Accuracy Score:', clf.score(X_test, y_test))
      print('Prediction:', y_pred)
      mscore.append(['Logistic Regression', clf.score(X_test, y_test)])
      print(classification_report(y_test, y_pred))
      confusion(y_test, y_pred)
     0.18044000000000082
     Accuracy Score: 0.7592875318066158
     Prediction: [0 1 0 ... 0 0 0]
                   precision
                                recall f1-score
                                                    support
                                  0.77
                0
                        0.90
                                             0.83
                                                       3056
                1
                        0.47
                                  0.70
                                             0.57
                                                        874
                                             0.76
                                                       3930
         accuracy
        macro avg
                        0.69
                                  0.74
                                             0.70
                                                       3930
     weighted avg
                        0.81
                                  0.76
                                             0.77
                                                       3930
     Confusion Matrix:
              Predict[0] Predict[1]
     True[0]
                    2368
                                  688
     True[1]
                     258
                                  616
[19]:
               Predict[0] Predict[1]
      True[0]
                     2368
                                  688
      True[1]
                      258
                                  616
[20]: from sklearn.ensemble import RandomForestClassifier
      from time import process_time
      rnd_clf = RandomForestClassifier(n_estimators=100, criterion='gini', u
       →random_state=12)
      start = process_time()
      model = rnd_clf.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      rf_prediction_proba = rnd_clf.predict_proba(X_test)[:, 1]
      y_pred = rnd_clf.predict(X_test)
      print('Accuracy Score:', rnd_clf.score(X_test, y_test))
      print('Prediction:', y_pred)
```

Accuracy Score: 0.789058524173028

Prediction: [0 0 0 ... 0 0 0]

	precision	recall	f1-score	support
0	0.85	0.89	0.87	3056
1	0.53	0.43	0.47	874
accuracy			0.79	3930
macro avg	0.69	0.66	0.67	3930
weighted avg	0.78	0.79	0.78	3930

Confubion nation.					
	Predict	[0]	Predict[1]		
True	e[0] 2	2727	329		
True	e[1]	500	374		
	Variable	Imp	ortance		
14	chem	0	. 205154		
7	grade	0	.091922		
2	age	0	.080710		
4	marry	0	.070751		
5	income	0	.064811		
3	size	0	.060049		
18	lung	0	.056253		
15	CEA	0	.054175		
9	T	0	.053338		
1	race	0	.041704		
10	N	0	.035928		
19	group	0	.032703		
0	gender	0	.031439		
6	site	0	.029272		
16	bone	0	.021990		
11	surgery_pri	0	.017856		
8	kind	0	.015665		
12	RX_Summ	0	.013605		
13	radiate	0	.013441		
17	brain	0	.009235		

```
[21]: from sklearn.ensemble import BaggingClassifier
      from sklearn.tree import DecisionTreeClassifier
      from time import process_time
      bagging = BaggingClassifier(base_estimator=__
       →DecisionTreeClassifier(random_state=12), max_samples = 1.0, max_features = 1.
       ⇔0,
                                  bootstrap = True, bootstrap_features = False,
       →random_state=12)
      start = process_time()
      bagging.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      bg_prediction_proba = bagging.predict_proba(X_test)[:, 1]
      y_pred = bagging.predict(X_test)
      print('Accuracy Score:', bagging.score(X_test, y_test))
      print('Prediction:', y_pred)
      mscore.append(['Bagging DecisionTree', bagging.score(X_test, y_test)])
      print(classification_report(y_test, y_pred))
      confusion(y_test, y_pred)
     0.6984320000000004
     Accuracy Score: 0.7699745547073792
     Prediction: [0 0 0 ... 0 0 0]
```

support	f1-score	recall	precision	
3056	0.86	0.88	0.83	0
874	0.43	0.39	0.48	1
3930	0.77			accuracy
3930	0.64	0.64	0.66	macro avg
3930	0.76	0.77	0.76	weighted avg

	Predict[0]	Predict[1]
True[0]	2682	374
True[1]	530	344
[21]:	Predict[0]	Predict[1]
True[0]	2682	374
True[1]	530	344

```
[22]: from sklearn.neighbors import KNeighborsClassifier
      from time import process_time
      knn = KNeighborsClassifier()
      start = process_time()
      knn.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      knn_prediction_proba = knn.predict_proba(X_test)[:, 1]
      y_pred = knn.predict(X_test)
      print('Accuracy Score:', knn.score(X_test, y_test))
      print('Prediction:', y_pred)
      mscore.append(['KNN', knn.score(X_test, y_test)])
      print(classification_report(y_test, y_pred))
      confusion(y_test, y_pred)
     0.007623999999999853
     Accuracy Score: 0.6961832061068702
     Prediction: [0 0 0 ... 0 0 0]
                   precision
                                recall f1-score
                                                    support
                        0.88
                                   0.71
                                             0.78
                0
                                                       3056
                1
                        0.39
                                   0.66
                                             0.49
                                                        874
         accuracy
                                             0.70
                                                       3930
                                   0.68
                                             0.64
                                                       3930
        macro avg
                        0.64
     weighted avg
                        0.77
                                   0.70
                                             0.72
                                                       3930
     Confusion Matrix:
              Predict[0] Predict[1]
     True[0]
                                  901
                    2155
     True[1]
                     293
                                  581
[22]:
               Predict[0] Predict[1]
      True[0]
                     2155
                                  901
      True[1]
                      293
                                  581
[23]: from sklearn.naive_bayes import GaussianNB
      from time import process_time
      gnb = GaussianNB()
```

```
start = process_time()
      gnb.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      gnb_prediction_proba = gnb.predict_proba(X_test)[:, 1]
      y_pred = gnb.predict(X_test)
      print('Accuracy Score:', gnb.score(X_test, y_test))
      print('Prediction:', y_pred)
      mscore.append(['Gaussian Naive Bayes', gnb.score(X_test, y_test)])
      print(classification_report(y_test, y_pred))
      confusion(y_test, y_pred)
     0.01813399999999632
     Accuracy Score: 0.6826972010178117
     Prediction: [0 1 0 ... 0 1 0]
                   precision
                              recall f1-score
                                                    support
                0
                        0.89
                                  0.67
                                             0.77
                                                       3056
                1
                        0.39
                                  0.72
                                             0.50
                                                        874
                                             0.68
                                                       3930
         accuracy
        macro avg
                        0.64
                                  0.70
                                             0.63
                                                       3930
     weighted avg
                        0.78
                                  0.68
                                             0.71
                                                       3930
     Confusion Matrix:
              Predict[0] Predict[1]
     True[0]
                    2053
                                1003
     True[1]
                     244
                                  630
[23]:
               Predict[0] Predict[1]
      True[0]
                     2053
                                 1003
      True[1]
                      244
                                  630
[24]: from sklearn.ensemble import GradientBoostingClassifier
      from time import process_time
      gbc = GradientBoostingClassifier(learning_rate=0.1, n_estimators=100,__
      →random_state=12)
      start = process_time()
      model = gbc.fit(X_train_sm, y_train_sm)
```

Accuracy Score: 0.8129770992366412

Prediction: [0 0 0 ... 0 0 0]

	precision	recall	f1-score	support
0	0.87	0.89	0.88	3056
1	0.58	0.55	0.57	874
accuracy			0.81	3930
macro avg	0.73	0.72	0.72	3930
weighted avg	0.81	0.81	0.81	3930

Confusion Matrix:

Predict[0] Predict[1] True[0] 2715 341 True[1] 394 480 Variable Importance 14 chem 0.433358 7 grade 0.102839 2 age 0.087997 18 0.059656 lung 4 0.047998 marry 9 Τ 0.044653 5 income 0.044059 0.042455 15 CEA 3 size 0.038965 11 surgery_pri 0.031851 19 group 0.025899 16 0.010312 bone

```
6
                site
                        0.004589
               brain
                        0.002841
     17
     13
             radiate
                        0.002317
     8
                kind
                        0.001537
                        0.000000
     0
              gender
[25]: from sklearn.ensemble import AdaBoostClassifier
      from time import process_time
      ada = AdaBoostClassifier(learning_rate=1.0, n_estimators=50, random_state=12)
      start = process_time()
      model = ada.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      ada_prediction_proba = ada.predict_proba(X_test)[:, 1]
      y_pred = ada.predict(X_test)
      print('Accuracy Score:', ada.score(X_test, y_test))
      print('Prediction:', y_pred)
      mscore.append(['Adaptive Boosting', ada.score(X_test, y_test)])
      # from sklearn.metrics import classification_report
      print(classification_report(y_test, y_pred))
      confusion(y_test, y_pred)
      print(pd.DataFrame({'Variable':X.columns,
                    'Importance':model.feature_importances_}).
       ⇔sort_values('Importance', ascending=False))
```

1

10

12

0.007346

0.006314

0.005013

race

RX_Summ

N

Accuracy Score: 0.8048346055979644

Prediction: [0 0 0 ... 0 0 0]

	precision	recall	f1-score	support
0	0.88	0.87	0.87	3056
1	0.56	0.58	0.57	874
accuracy			0.80	3930
macro avg	0.72	0.73	0.72	3930
weighted avg	0.81	0.80	0.81	3930

```
True[0]
                     2653
                                  403
     True[1]
                      364
                                  510
            Variable Importance
     5
              income
                             0.22
                             0.20
     4
               marry
                             0.12
     18
                lung
                             0.12
     15
                  CEA
     2
                             0.08
                 age
     3
                size
                             0.06
     16
                             0.06
                bone
     7
               grade
                             0.04
     10
                             0.02
     14
                             0.02
                chem
     6
                             0.02
                site
     11
         surgery_pri
                             0.02
     12
             RX_Summ
                             0.02
     17
                             0.00
               brain
     0
              gender
                             0.00
                             0.00
     13
             radiate
                             0.00
     1
                race
     9
                             0.00
     8
                kind
                             0.00
     19
                             0.00
               group
[26]: from sklearn.svm import SVC
      from time import process_time
      svm_clf = SVC(kernel='rbf', gamma='scale', probability=True, random_state=12)
      start = process_time()
      svm_clf.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      svm_prediction_proba = svm_clf.predict_proba(X_test)[:, 1]
      y_pred = svm_clf.predict(X_test)
      print('Accuracy Score:', svm_clf.score(X_test, y_test))
      print('Prediction:', y_pred)
      mscore.append(['SVM', svm_clf.score(X_test, y_test)])
      # from sklearn.metrics import classification_report
      print(classification_report(y_test, y_pred))
      confusion(y_test, y_pred)
```

Predict[0] Predict[1]

Accuracy Score: 0.7580152671755725

Prediction: [0 1 0 ... 0 0 0]

support	f1-score	recall	precision	
3056	0.83	0.78	0.90	0
874	0.56	0.70	0.47	1
3930	0.76			accuracy
3930	0.70	0.74	0.68	macro avg
3930	0.77	0.76	0.80	weighted avg

Confusion Matrix:

Predict[0] Predict[1]
True[0] 2371 685
True[1] 266 608

[26]: Predict[0] Predict[1] True[0] 2371 685 True[1] 266 608

```
[27]: from xgboost import XGBClassifier
      from time import process_time
      xgbc = XGBClassifier(eta=0.3, max_depth=6, random_state=12)
      start = process_time()
      model = xgbc.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      xgbc_prediction_proba = xgbc.predict_proba(X_test)[:, 1]
      y_pred = xgbc.predict(X_test)
      print('Accuracy Score:', xgbc.score(X_test, y_test))
      print('Prediction:', y_pred)
      mscore.append(['XGBoost', xgbc.score(X_test, y_test)])
      from sklearn.metrics import classification_report
      print(classification_report(y_test, y_pred))
      confusion(y_test, y_pred)
      print(pd.DataFrame({'Variable':X.columns,
                    'Importance':model.feature_importances_}).
       ⇔sort_values('Importance', ascending=False))
```

8.497627000000023

Accuracy Score: 0.8048346055979644

Prediction: [0 0 0 ... 0 0 0]

	precision	recall	f1-score	support
0	0.85	0.91	0.88	3056
1	0.58	0.44	0.50	874
accuracy			0.80	3930
macro avg	0.72	0.67	0.69	3930
weighted avg	0.79	0.80	0.79	3930

```
Predict[0] Predict[1]
True[0]
               2778
                             278
True[1]
                 489
                             385
       Variable Importance
14
           chem
                    0.344881
11
   surgery_pri
                    0.098779
2
                    0.075192
            age
18
           lung
                    0.059739
7
          grade
                    0.049362
15
            CEA
                    0.046022
5
         income
                    0.044570
4
          marry
                    0.041657
9
              Τ
                    0.040148
16
                    0.031390
           bone
3
                    0.028152
           size
19
          group
                    0.025421
1
                    0.020828
           race
10
              N
                    0.020576
12
        RX_Summ
                    0.020220
13
        radiate
                    0.012359
17
          brain
                    0.012105
6
           site
                    0.011551
8
                    0.009906
           kind
0
         gender
                    0.007143
```

```
mlp_prediction_proba = mlp.predict_proba(X_test)[:, 1]
      mlp_pred_diabetes = mlp.predict(X_test)
      print('Accuracy Score:', mlp.score(X_test, y_test))
      print('Prediction:', mlp_pred_diabetes)
      print("parameter: ", mlp.get_params())
      mscore.append(['MLP', mlp.score(X_test, y_test)])
     46.838952000000006
     Accuracy Score: 0.761323155216285
     Prediction: [0 0 0 ... 0 0 0]
     parameter: {'activation': 'relu', 'alpha': 0.0001, 'batch size': 'auto',
     'beta_1': 0.9, 'beta_2': 0.999, 'early_stopping': False, 'epsilon': 1e-08,
     'hidden_layer_sizes': (100,), 'learning_rate': 'constant', 'learning_rate_init':
     0.001, 'max_fun': 15000, 'max_iter': 200, 'momentum': 0.9, 'n_iter_no_change':
     10, 'nesterovs momentum': True, 'power_t': 0.5, 'random_state': 12, 'shuffle':
     True, 'solver': 'adam', 'tol': 0.0001, 'validation_fraction': 0.1, 'verbose':
     False, 'warm_start': False}
     /Users/zhiyi/opt/anaconda3/lib/python3.9/site-
     packages/sklearn/neural_network/_multilayer_perceptron.py:692:
     ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
     the optimization hasn't converged yet.
       warnings.warn(
[29]: mscore.sort(key=lambda x: x[1], reverse=True)
      mscore
[29]: [['Gradient Boosting', 0.8129770992366412],
       ['Adaptive Boosting', 0.8048346055979644],
       ['XGBoost', 0.8048346055979644],
       ['Random Forest', 0.789058524173028],
       ['Bagging DecisionTree', 0.7699745547073792],
       ['MLP', 0.761323155216285],
       ['Logistic Regression', 0.7592875318066158],
       ['SVM', 0.7580152671755725],
       ['KNN', 0.6961832061068702],
       ['Gaussian Naive Bayes', 0.6826972010178117]]
[30]: model = list(i[0] for i in mscore)
      score = list(round(i[1]*100,2) for i in mscore)
      print('Accuracy Score: \n')
      for m,s in zip(model, score):
          print(f'{m}: {s}%')
```

```
# creating horizontal bar
plt.barh(model, score, height = 0.5, color='#4B4E6D')

plt.xlabel("Accuracy Score (%)")
plt.ylabel("Model")
plt.title("Model Comparison regarding Accuracy")
plt.gca().invert_yaxis()
plt.rc('font', size=9)
plt.show()
```

Accuracy Score:

Gradient Boosting: 81.3% Adaptive Boosting: 80.48%

XGBoost: 80.48%

Random Forest: 78.91%

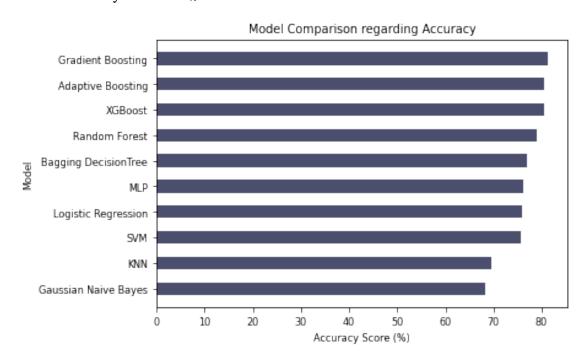
Bagging DecisionTree: 77.0%

MLP: 76.13%

Logistic Regression: 75.93%

SVM: 75.8% KNN: 69.62%

Gaussian Naive Bayes: 68.27%



```
[31]: rf_prediction_proba = rnd_clf.predict_proba(X_test)[:, 1]
      def roc_curve_and_score(y_test, pred_proba):
          fpr, tpr, _ = roc_curve(y_test.ravel(), pred_proba.ravel())
          roc_auc = roc_auc_score(y_test.ravel(), pred_proba.ravel())
          return fpr, tpr, roc_auc
      from sklearn.metrics import roc_auc_score, roc_curve
      import matplotlib
      import matplotlib.pyplot as plt
      plt.figure(figsize=(9, 7))
      matplotlib.rcParams.update({'font.size': 15})
      plt.grid()
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, rf_prediction_proba)
      plt.plot(fpr, tpr, color='darkorange', lw=2,
               label='Random Forest={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, gbc_prediction_proba)
      plt.plot(fpr, tpr, color='green', lw=2,
               label='Gradient Boosting={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, xgbc_prediction_proba)
      plt.plot(fpr, tpr, color='purple', lw=2,
               label='XGBoost={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, svm_prediction_proba)
      plt.plot(fpr, tpr, color='sienna', lw=2,
               label='SVM={0:.3f}'.format(roc auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, mlp_prediction_proba)
      plt.plot(fpr, tpr, color='blue', lw=2,
               label='MLP={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, ada_prediction_proba)
      plt.plot(fpr, tpr, color='yellow', lw=2,
               label='AdaBoost={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, knn_prediction_proba)
      plt.plot(fpr, tpr, color='grey', lw=2,
               label='KNN={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, gnb_prediction_proba)
      plt.plot(fpr, tpr, color='purple', lw=2,
               label='Gaussian Naive Bayes={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, bg_prediction_proba)
      plt.plot(fpr, tpr, color='cyan', lw=2,
               label='Bagging Decision Trees={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, clf_prediction_proba)
      plt.plot(fpr, tpr, color='crimson', lw=2,
               label='Logistic Regression={0:.3f}'.format(roc_auc))
      plt.plot([0, 1], [0, 1], color='navy', lw=1, linestyle='--')
      plt.legend(loc="lower right")
      plt.xlim([0.0, 1.0])
      plt.ylim([0.0, 1.05])
```

```
plt.xlabel('1 - Specificity')
plt.ylabel('Sensitivity')
plt.show()
```

