KNN_drug_classification

February 28, 2025

```
[]:
[289]: import pandas as pd
       import numpy as np
       import matplotlib.pyplot as plt
       import seaborn as sns
       from sklearn.model_selection import train_test_split
       from sklearn.neighbors import KNeighborsClassifier
       from sklearn.metrics import accuracy_score, r2_score, mean_squared_error, __
        →mean_absolute_error
       from sklearn.preprocessing import StandardScaler
       from sklearn.model_selection import cross_val_score
       from sklearn.model_selection import GridSearchCV
[290]: url = r"D:\Supervised Machine Learning lab (SMLL)\6\Practice dataset 2_
        →KNNClassifier drug_classification.csv"
       df = pd.read_csv(url)
[291]: df.info()
      <class 'pandas.core.frame.DataFrame'>
      RangeIndex: 200 entries, 0 to 199
      Data columns (total 6 columns):
           Column
                        Non-Null Count
                                        Dtype
                        _____
           _____
                        200 non-null
       0
                                         int64
           Age
       1
           Sex
                        200 non-null
                                        object
       2
                        200 non-null
                                        object
       3
           Cholesterol 200 non-null
                                        object
       4
           Na_to_K
                        200 non-null
                                         float64
                        200 non-null
           Drug_Type
                                         object
      dtypes: float64(1), int64(1), object(4)
      memory usage: 9.5+ KB
[292]: df.head()
[292]:
                       BP Cholesterol Na_to_K Drug_Type
          Age Sex
       0
           23
                F
                                 HIGH
                                        25.355
                     HIGH
                                                   DrugY
```

```
1
           47
                 Μ
                       LOW
                                   HIGH
                                          13.093
                                                      drugC
       2
           47
                       LOW
                                   HIGH
                                           10.114
                                                      drugC
                 М
       3
           28
                 F
                    NORMAL
                                   HIGH
                                           7.798
                                                      drugX
       4
                 F
                                           18.043
           61
                       LOW
                                   HIGH
                                                      DrugY
[293]:
       df.describe(include='all')
[293]:
                                                         Na_to_K Drug_Type
                            Sex
                                    BP Cholesterol
                       Age
                                                     200.000000
               200.000000
                            200
                                   200
                                                200
                                                                        200
       count
                                                  2
       unique
                       NaN
                               2
                                     3
                                                                          5
                                                             NaN
       top
                       NaN
                                 HIGH
                                               HIGH
                                                             NaN
                                                                     DrugY
                       NaN
                            104
                                    77
                                                103
                                                             NaN
                                                                         91
       freq
       mean
                 44.315000 NaN
                                   NaN
                                                NaN
                                                      16.084485
                                                                       NaN
       std
                 16.544315 NaN
                                   NaN
                                                NaN
                                                       7.223956
                                                                       NaN
       min
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                                   NaN
                                                NaN
                                                       6.269000
                                                                       NaN
       25%
                 31.000000 NaN
                                   NaN
                                                {\tt NaN}
                                                      10.445500
                                                                       NaN
       50%
                 45.000000 NaN
                                                                       NaN
                                   NaN
                                                NaN
                                                      13.936500
       75%
                                   NaN
                                                                       NaN
                 58.000000
                            {\tt NaN}
                                                {\tt NaN}
                                                      19.380000
       max
                 74.000000 NaN
                                   NaN
                                                NaN
                                                      38.247000
                                                                       NaN
[294]: from sklearn.preprocessing import LabelEncoder
       le = LabelEncoder()
[295]: # Encode categorical columns
       df['Sex'] = le.fit_transform(df['Sex'])
       df['BP'] = le.fit_transform(df['BP'])
       df['Cholesterol'] = le.fit_transform(df['Cholesterol'])
       df['Drug_Type'] = le.fit_transform(df['Drug_Type'])
       # Display the updated dataframe
       df.head()
[295]:
          Age
               Sex
                    BP
                         Cholesterol Na_to_K Drug_Type
           23
                                        25.355
       0
                  0
                      0
                                    0
                                                          0
       1
           47
                  1
                      1
                                    0
                                        13.093
                                                          3
       2
           47
                                        10.114
                                                          3
                  1
                      1
                                    0
       3
           28
                      2
                                         7.798
                                                          4
                  0
                                    0
       4
           61
                  0
                      1
                                    0
                                        18.043
                                                          0
[296]: X = df.drop('Drug_Type', axis=1)
       y = df['Drug_Type']
[297]: | x = pd.get_dummies(X, drop_first=True)
[298]: sc = StandardScaler()
       x = sc.fit_transform(x)
[299]: x
```

```
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[-1.35218642, -1.040833, -1.11016894, 1.03046381, 0.93444819],
[0.88984349, -1.040833, 1.32976279, -0.97043679, -0.30537382],
[-1.47337723, -1.040833, 0.10979693, 1.03046381, -0.61040279],
[-0.50385078, -1.040833, -1.11016894, 1.03046381, -0.08250007],
[-1.59456803, -1.040833, -1.11016894, -0.97043679, 2.92865486],
[0.76865269, -1.040833, 1.32976279, 1.03046381, 1.36118344],
[1.55639293, 0.96076892, -1.11016894, -0.97043679, -0.86533373],
[0.16269866, 0.96076892, -1.11016894, -0.97043679, -0.788452],
```

```
[ 1.25341591, 0.96076892, -1.11016894, 1.03046381, 2.62459732],
              [1.19282051, 0.96076892, -1.11016894, 1.03046381, 0.67271724],
              [0.82924809, 0.96076892, -1.11016894, -0.97043679, 0.40335363],
             [-1.29159102, 0.96076892, -1.11016894, -0.97043679, -1.12040345],
             [1.67758373, 0.96076892, 0.10979693, -0.97043679, 0.031296],
             [1.67758373, 0.96076892, 0.10979693, -0.97043679, -1.29276286],
              [0.10210325, -1.040833, -1.11016894, -0.97043679, 2.58143808],
             [0.70805729, -1.040833, 0.10979693, -0.97043679, -0.6269171],
             [-1.71575884, 0.96076892, 0.10979693, -0.97043679, -0.56599457],
              [0.46567567, 0.96076892, 1.32976279, -0.97043679, -0.85908883],
              [-1.29159102, 0.96076892, 1.32976279, 1.03046381, -0.28650033],
              [-0.26146916, -1.040833 , 0.10979693, 1.03046381, -0.6571702 ]])
[300]: X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3,__
        →random_state=42, shuffle=True)
[301]: params = {
           'n_neighbors':np.array(range(1, 50)),
           'weights' : ['uniform', 'distance'],
           'metric':['minkowski','manhattan','euclidean']
      }
[302]: from sklearn.neighbors import KNeighborsClassifier
      dia_reg = GridSearchCV(KNeighborsClassifier(), params, cv = 10)
[303]: dia_reg.fit(X_train, y_train)
[303]: GridSearchCV(cv=10, estimator=KNeighborsClassifier(),
                   param_grid={'metric': ['minkowski', 'manhattan', 'euclidean'],
                                'n_neighbors': array([ 1, 2, 3, 4, 5, 6, 7, 8,
      9, 10, 11, 12, 13, 14, 15, 16, 17,
             18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34,
             35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49]),
                               'weights': ['uniform', 'distance']})
[304]: dia_reg.best_score_
[304]: 0.8928571428571429
[305]: dia_reg.best_params_
[305]: {'metric': 'manhattan', 'n_neighbors': 21, 'weights': 'distance'}
[306]: regressor = KNeighborsClassifier(metric = 'manhattan', n_neighbors= 21,__
       ⇔weights='distance')
      regressor.fit(X_train, y_train)
[306]: KNeighborsClassifier(metric='manhattan', n_neighbors=21, weights='distance')
```

```
[307]: y_pred = regressor.predict(X_test)
[308]: from sklearn.metrics import accuracy_score
       # Calculate and display accuracy score
      print("Accuracy score : {:.4f}".format(accuracy_score(y_test, y_pred)))
      Accuracy score: 0.9167
[309]: from sklearn.metrics import confusion_matrix, classification_report
      # Evaluate the model
      print("Confusion Matrix:")
      print(confusion_matrix(y_test, y_pred))
      print("\nClassification Report:")
      print(classification_report(y_test, y_pred))
      print("\nAccuracy Score:")
      print(accuracy_score(y_test, y_pred))
      Confusion Matrix:
      [[24 0 2 0 0]
       [0 7 0 0 0]
       [0 0 3 0 0]
       [2 0 0 3 1]
       [000018]]
      Classification Report:
                    precision
                                recall f1-score
                                                    support
                 0
                                   0.92
                         0.92
                                             0.92
                                                         26
                         1.00
                                   1.00
                                             1.00
                 1
                                                          7
                 2
                         0.60
                                   1.00
                                             0.75
                                                          3
                         1.00
                                   0.50
                 3
                                             0.67
                                                          6
                 4
                         0.95
                                   1.00
                                             0.97
                                                         18
                                             0.92
                                                         60
          accuracy
         macro avg
                         0.89
                                   0.88
                                             0.86
                                                         60
      weighted avg
                         0.93
                                   0.92
                                             0.91
                                                         60
      Accuracy Score:
      0.916666666666666
[310]: # Plot the regplot for the predictions
      sns.regplot(x=y_test, y=y_pred)
      plt.xlabel('Actual Drug Type')
      plt.ylabel('Predicted Drug Type')
      plt.title('Actual vs Predicted Drug Type')
      plt.show()
```



