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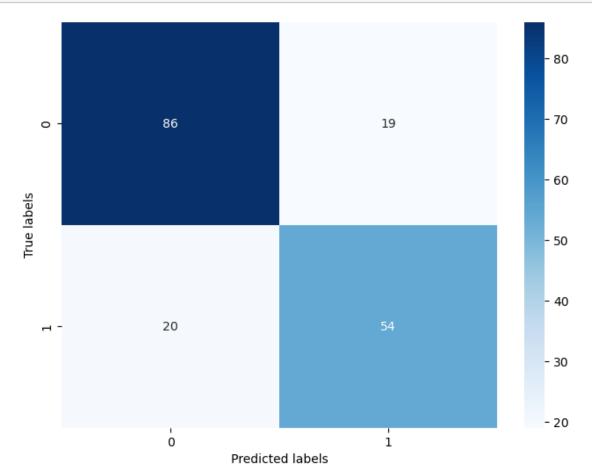
January 23, 2025

```
[1]: 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.preprocessing import StandardScaler
     from sklearn.neighbors import KNeighborsClassifier
     from sklearn.neighbors import KNeighborsRegressor
     from sklearn.metrics import accuracy_score, classification_report, u
      confusion matrix, mean squared error, mean absolute error, r2 score
[2]: # Load Titanic dataset
     data = pd.read_csv(r"C:\Users\91703\OneDrive\Desktop\TITANIC.csv")
[3]:
    data.head()
[3]:
        PassengerId
                     Survived
                               Pclass
     0
                             0
                                     3
                  1
                  2
     1
                             1
                                     1
                  3
     2
                             1
                                     3
     3
                  4
                                     1
                             1
                             0
                                     3
     4
                  5
                                                       Name
                                                                           SibSp \
                                                                Sex
                                                                      Age
     0
                                   Braund, Mr. Owen Harris
                                                               male
                                                                    22.0
                                                                                1
     1
        Cumings, Mrs. John Bradley (Florence Briggs Th... female
                                                                              1
     2
                                    Heikkinen, Miss. Laina
                                                             female
                                                                               0
     3
             Futrelle, Mrs. Jacques Heath (Lily May Peel)
                                                             female
                                                                     35.0
                                                                                1
     4
                                  Allen, Mr. William Henry
                                                                    35.0
                                                                                0
                                                               male
        Parch
                                     Fare Cabin Embarked
                          Ticket
     0
            0
                      A/5 21171
                                   7.2500
                                            NaN
                                                        S
                                                        С
                       PC 17599
                                  71.2833
                                            C85
     1
            0
     2
                                                        S
            0
               STON/02. 3101282
                                  7.9250
                                            NaN
     3
                                  53.1000
                                           C123
                                                        S
                          113803
            0
                          373450
                                   8.0500
                                            NaN
                                                        S
```

```
[22]: data.info()
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 891 entries, 0 to 890
     Data columns (total 6 columns):
          Column Non-Null Count Dtype
                  891 non-null
                                  float64
      0
          Age
                  891 non-null
                                  int64
      1
          Pclass
          Sex
                  891 non-null
                                  int64
      3
          SibSp
                  891 non-null
                                  int64
      4
          Parch
                  891 non-null
                                  int64
          Fare
                  891 non-null
                                  float64
     dtypes: float64(2), int64(4)
     memory usage: 41.9 KB
[23]: data.describe()
[23]:
                    Age
                             Pclass
                                            Sex
                                                       SibSp
                                                                   Parch
                                                                                Fare
      count 891.000000 891.000000
                                     891.000000 891.000000
                                                             891.000000 891.000000
      mean
              29.699118
                           2.308642
                                       0.352413
                                                   0.523008
                                                                0.381594
                                                                           32.204208
      std
              13.002015
                           0.836071
                                       0.477990
                                                   1.102743
                                                                0.806057
                                                                           49.693429
     min
              0.420000
                           1.000000
                                       0.000000
                                                   0.000000
                                                                0.000000
                                                                            0.000000
      25%
              22.000000
                           2.000000
                                       0.000000
                                                   0.000000
                                                                0.000000
                                                                            7.910400
      50%
              29.699118
                           3.000000
                                       0.000000
                                                   0.000000
                                                                0.000000
                                                                           14.454200
      75%
              35.000000
                           3.000000
                                       1.000000
                                                   1.000000
                                                                0.000000
                                                                           31.000000
              80.000000
                           3.000000
                                       1.000000
                                                   8.000000
                                                                6.000000
                                                                          512.329200
      max
 [4]: # Select relevant columns columns and convert categorical variables
      data = data[['Survived', 'Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare']]
      data['Sex'] = data['Sex'].map({'male': 0, 'female': 1})
 [5]: # Handle missing Age values
      data['Age'] = pd.to_numeric(data['Age'], errors='coerce')
      data['Age'] = data['Age'].fillna(data['Age'].mean())
 [6]: # Define target variable (y) and feature variables (X)
      y = data['Survived']
      X = data[['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare']]
 [7]: # Scale features using StandardScaler
      from sklearn.preprocessing import StandardScaler
      scaler = StandardScaler()
      X_scaled = scaler.fit_transform(X)
 [8]: # Split data into training and testing sets
      from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,
                        →random_state=42)
   [9]: # Create and train KNN Classifier model
                    from sklearn.neighbors import KNeighborsClassifier
                    model = KNeighborsClassifier(n_neighbors=5)
                    model.fit(X_train, y_train)
   [9]: KNeighborsClassifier()
[10]: # Make predictions on test data
                    y_pred = model.predict(X_test)
                    print(y_pred)
                   \begin{smallmatrix} \mathsf{I} \mathsf{O} & \mathsf{O} & \mathsf{O} & \mathsf{I} & \mathsf{O} & \mathsf{O} & \mathsf{O} & \mathsf{O} & \mathsf{O} & \mathsf{O} & \mathsf{I} & \mathsf{O} & \mathsf{I} & \mathsf{I} & \mathsf{I} & \mathsf{I} & \mathsf{I} & \mathsf{O} & \mathsf{O} & \mathsf{O} & \mathsf{O} & \mathsf{I} & \mathsf{O} & \mathsf{I} & \mathsf{O} & \mathsf{I} & \mathsf{I} & \mathsf{I} & \mathsf{I} & \mathsf{I} & \mathsf{O} & \mathsf{O} & \mathsf{O} & \mathsf{O} & \mathsf{I} & \mathsf{O} & \mathsf{I} & \mathsf{O} & \mathsf{I} & \mathsf{I} & \mathsf{I} & \mathsf{I} & \mathsf{I} & \mathsf{I} & \mathsf{O} &
                     1 0 0 0 0 1 0 0 1 1 1 1 1 0 0 0 1 0 0 1 0 0 0 1 1 1 1 0 0 0 1 1]
[11]: # Evaluate model performance
                    from sklearn.metrics import accuracy_score, classification_report,_
                      ⇔confusion_matrix
                    accuracy = accuracy_score(y_test, y_pred)
                    print("Accuracy:", accuracy)
                    print("Classification Report:", classification_report(y_test, y_pred))
                    print("Confusion Matrix:", confusion_matrix(y_test, y_pred))
                  Accuracy: 0.7821229050279329
                  Classification Report:
                                                                                                                                                                                        recall f1-score
                                                                                                                                             precision
                                                                                                                                                                                                                                                         support
                                                      0
                                                                                 0.81
                                                                                                                  0.82
                                                                                                                                                    0.82
                                                                                                                                                                                         105
                                                      1
                                                                                 0.74
                                                                                                                  0.73
                                                                                                                                                    0.73
                                                                                                                                                                                            74
                                                                                                                                                    0.78
                                                                                                                                                                                         179
                               accuracy
                           macro avg
                                                                                 0.78
                                                                                                                  0.77
                                                                                                                                                    0.77
                                                                                                                                                                                         179
                                                                                                                  0.78
                                                                                                                                                    0.78
                  weighted avg
                                                                                 0.78
                                                                                                                                                                                         179
                  Confusion Matrix: [[86 19]
                     [20 54]]
[12]: # Plot Confusion Matrix
                    import matplotlib.pyplot as plt
                    import seaborn as sns
                    plt.figure(figsize=(8, 6))
                    sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, cmap='Blues')
                    plt.xlabel("Predicted labels")
```

```
plt.ylabel("True labels")
plt.show()
```



```
[13]: # Select relevant columns columns and convert categorical variables
    data = data[['Age', 'Pclass', 'Sex', 'SibSp', 'Parch', 'Fare']]

[14]: # Define target variable (y) and feature variables (X)
    y = data['Age']
    X = data[['Pclass', 'Sex', 'SibSp', 'Parch', 'Fare']]

[15]: # Scale features using StandardScaler
    from sklearn.preprocessing import StandardScaler
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
[16]: # Split data into training and testing sets
    from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,_
       →random state=42)
[17]: # Create and train KNN Regressor model
      from sklearn.neighbors import KNeighborsRegressor
      model = KNeighborsRegressor(n_neighbors=5)
      model.fit(X_train, y_train)
[17]: KNeighborsRegressor()
[18]: # Make predictions on test data
      y_pred = model.predict(X_test)
      print(y pred)
     Γ21.2
                  31.4
                              28.8
                                           33.6
                                                       25.03982353 34.93982353
      26.41947059 30.07964706 26.41947059 21.6
                                                       28.8
                                                                   29.33982353
      14.22964706 31.91947059 29.
                                           33.53982353 28.8
                                                                   23.47964706
                  34.47964706 30.01947059 50.8
                                                       24.1
                                                                   27.2
      27.55929412 9.53982353 39.97964706 29.
                                                        9.53982353 25.47964706
      30.01947059 26.41947059 39.13982353 24.27964706 29.33982353 29.07964706
      41.47964706 26.41947059 43.8
                                           30.01947059 32.3
                                                                   22.33982353
      29.33982353 31.85929412 10.6
                                           26.63982353 32.07964706 27.2
      29.6
                  15.784
                                                       36.33982353 21.384
                              15.1
                                           45.
      31.85929412 37.2
                              31.4
                                           33.4
                                                       36.4
                                                                   25,47964706
      23.87964706 33.6
                              28.6
                                           42.73982353 31.85929412 36.4
      30.8
                  27.61947059 22.2
                                           49.8
                                                       21.4
                                                                   22.4
      45.27964706 45.
                              28.2
                                           28.67964706 26.41947059 29.53982353
                                           36.4
                                                       42.13982353 29.17964706
      33.6
                  13.73982353 6.4
      39.13982353 34.47964706 27.53982353 24.53982353 34.27964706 32.53982353
                              39.33982353 29.17964706 30.01947059 28.2
      26.73982353 8.2
      28.8
                  29.33982353 33.6
                                           30.01947059 42.73982353 32.6
      41.6
                  29.6
                              29.33982353 24.53982353 21.4
                                                                   39.27964706
      28.73982353 39.13982353 31.8
                                           32.53982353 41.6
                                                                   49.4
      30.33982353 25.93982353 41.47964706 29.
                                                       21.4
                                                                   35.33982353
       1.7
                  34.93982353 49.8
                                                       32.53982353 50.8
                                           27.8
      43.8
                  37.53982353 30.11947059 29.33982353 25.47964706 21.2
      29.69911765 21.8
                              30.4
                                           30.11947059 32.8
                                                                   23.87964706
      26.33982353 30.47964706 27.93982353 28.6
                                                                   37.8
                                                       29.
      39.4
                              29.
                                           31.4
                                                       29.93982353 29.33982353
      24.73982353 26.33982353 24.4
                                           30.47964706 29.33982353 29.6
      29.07964706 23.13982353 28.6
                                           24.8
                                                       25.97964706 50.8
      29.
                  49.8
                              27.93982353 46.6
                                                       31.4
                                                                   31.8
      30.01947059 29.6
                                           15.4
                              46.6
                                                       49.4
                                                                   24.8
      32.6
                  31.91947059 39.4
                                           36.4
                                                       24.93982353]
[19]: # Evaluate model performance
```

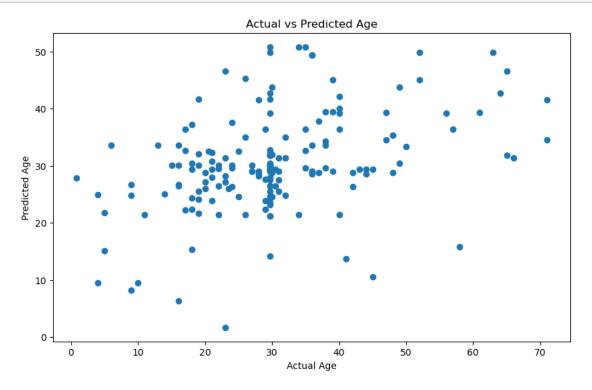
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

```
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print("Mean Squared Error:", mse)
print("Mean Absolute Error:", mae)
print("R-squared:", r2)
```

Mean Squared Error: 151.8969616344165 Mean Absolute Error: 9.10054682878738

R-squared: 0.1028520064418863

```
[20]: # Plot actual vs predicted values
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred)
plt.xlabel("Actual Age")
plt.ylabel("Predicted Age")
plt.title("Actual vs Predicted Age")
plt.show()
```



```
[21]: # Plot residuals
  residuals = y_test - y_pred
  plt.figure(figsize=(10, 6))
  plt.scatter(y_test, residuals)
  plt.xlabel("Actual Age")
```

```
plt.ylabel("Residuals")
plt.title("Residual Plot")
plt.show()
```

