teytitqsb

April 17, 2024

[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, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,␣
↪classification_report
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as IMBPipeline
```

[ ]:
```
```

[20]:
```
# Load the dataset
data = pd.read_csv("C:\\Users\\krestty\\Downloads\\archive (5)\\processed-data.
↪csv")

# Display the first few rows of the dataframe
print(data.head())
```

```
   Tiredness  Dry-Cough  Difficulty-in-Breathing  Sore-Throat  None_Sympton  \
0          1          1                        1            1             0
1          1          1                        1            1             0
2          1          1                        1            1             0
3          1          1                        1            1             0
4          1          1                        1            1             0

   Pains  Nasal-Congestion  Runny-Nose  None_Experiencing  Age_0-9  Age_10-19  \
0      1                 1           1                  0        1          0
1      1                 1           1                  0        1          0
2      1                 1           1                  0        1          0
3      1                 1           1                  0        1          0
4      1                 1           1                  0        1          0

   Age_20-24  Age_25-59  Age_60+  Gender_Female  Gender_Male  Severity_Mild  \
0          0          0        0              0            1              1
```

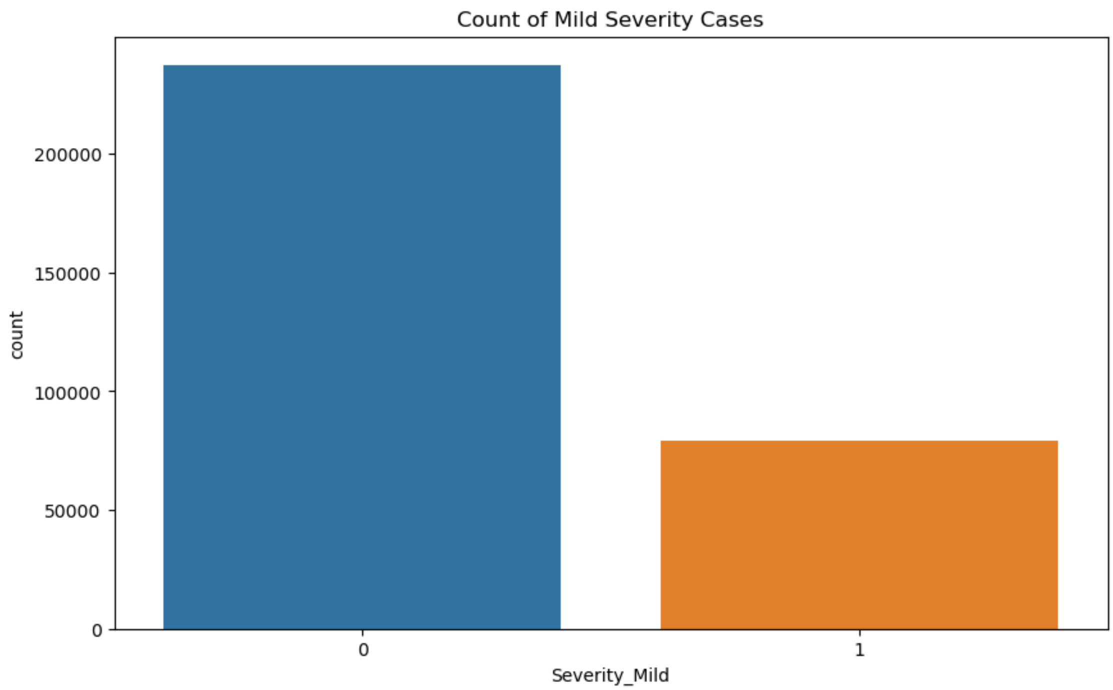
```
1           0           0         0              0            1              1
2           0           0         0              0            1              1
3           0           0         0              0            1              0
4           0           0         0              0            1              0

   Severity_Moderate  Severity_None
0                  0              0
1                  0              0
2                  0              0
3                  1              0
4                  1              0
```

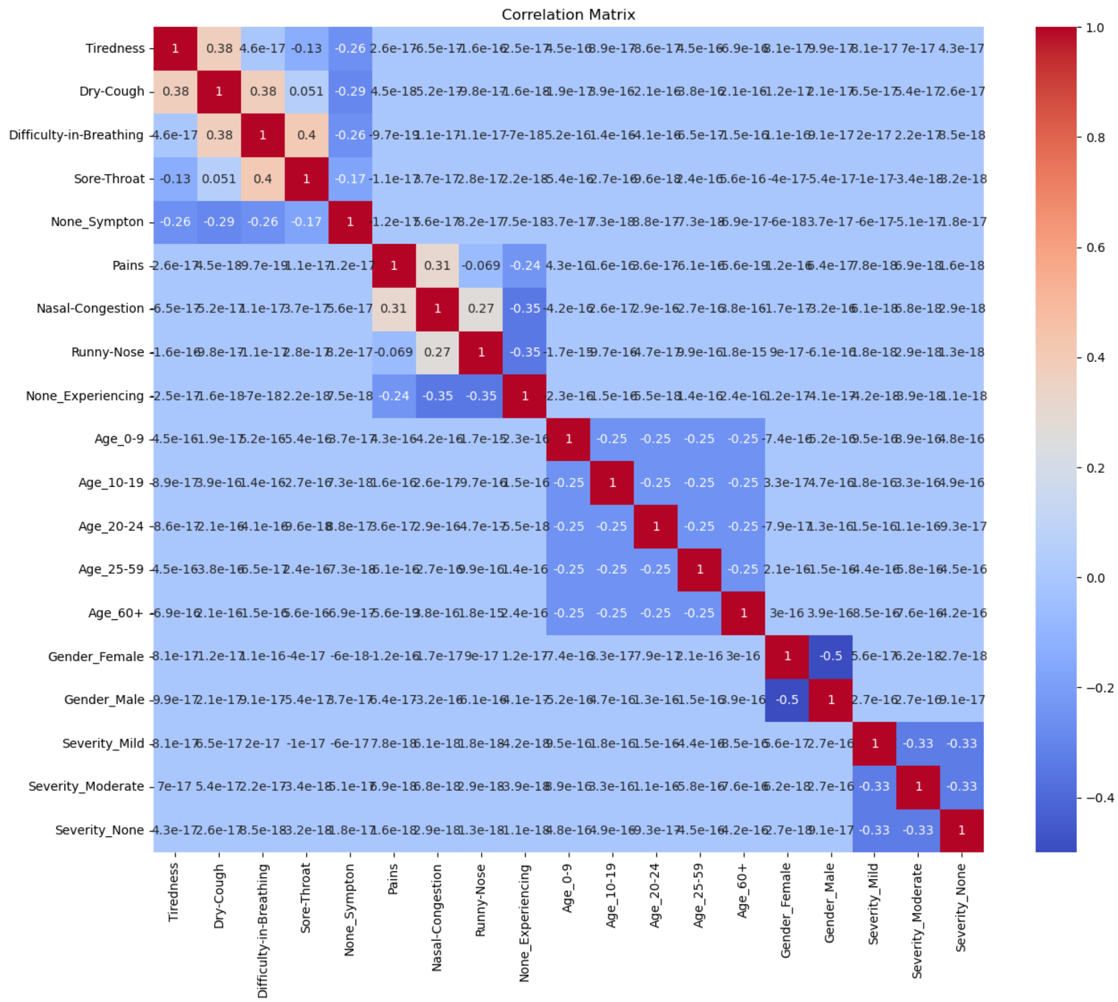
[9]:

```python
# Check for missing values in each column
missing_values = data.isnull().sum()
print("Missing values in each column:\n", missing_values)

# Handle missing values
# Assuming mean imputation is suitable based on the dataset's characteristics
data.fillna(data.mean(), inplace=True)  # Fill numerical missing values with␣
 ↪the mean

# Alternatively, if there are categorical columns with missing values, consider␣
 ↪using the mode:
# data['category_column'].fillna(data['category_column'].mode()[0],␣
 ↪inplace=True)
```

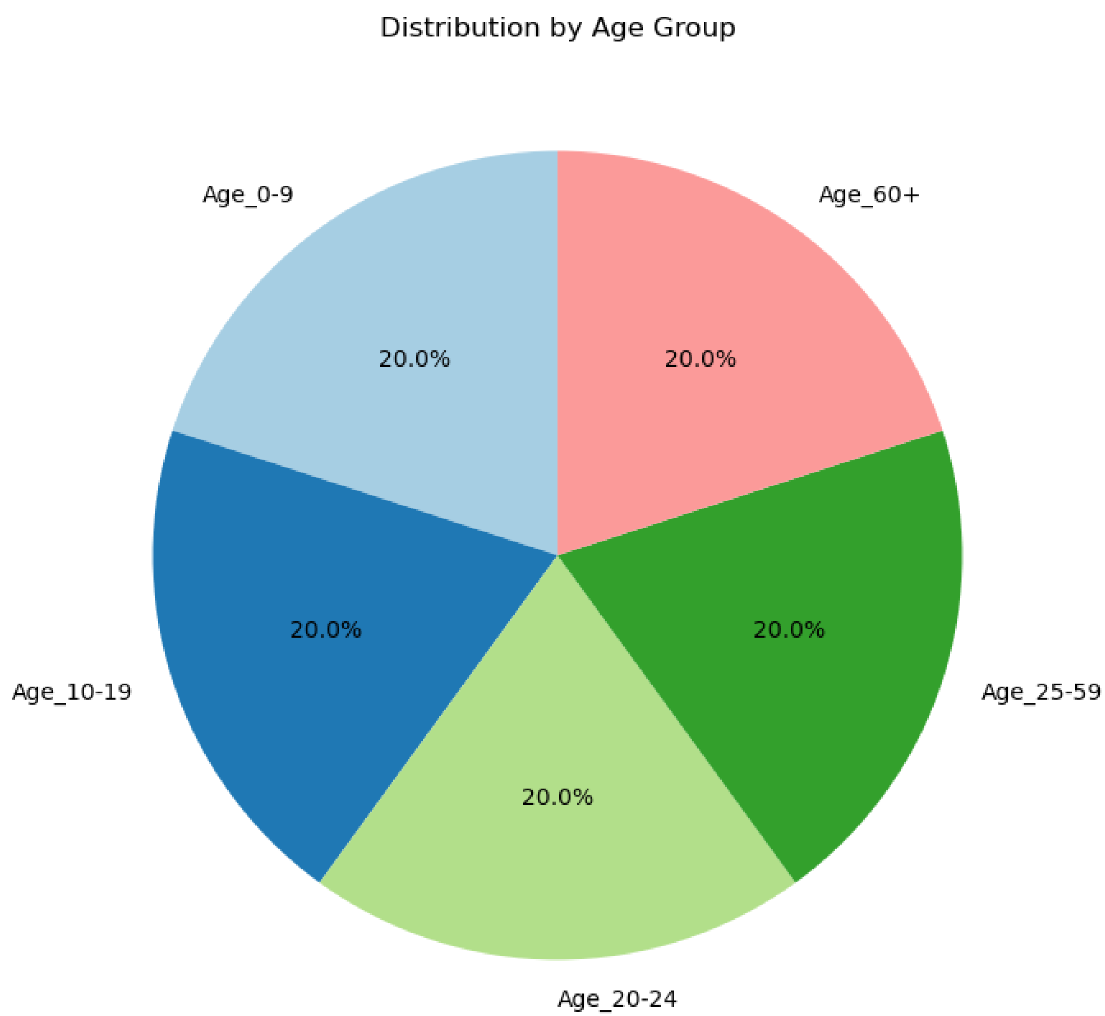
```
Missing values in each column:
 Tiredness                   0
Dry-Cough                   0
Difficulty-in-Breathing     0
Sore-Throat                 0
None_Sympton                0
Pains                       0
Nasal-Congestion            0
Runny-Nose                  0
None_Experiencing           0
Age_0-9                     0
Age_10-19                   0
Age_20-24                   0
Age_25-59                   0
Age_60+                     0
Gender_Female               0
Gender_Male                 0
Severity_Mild               0
Severity_Moderate           0
Severity_None               0
dtype: int64
```

[5]:
```python
# Visualizing the distribution of key variables
plt.figure(figsize=(10, 6))
sns.countplot(x='Severity_Mild', data=data)
plt.title('Count of Mild Severity Cases')
plt.show()

# Correlation heatmap
plt.figure(figsize=(15, 12))
sns.heatmap(data.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

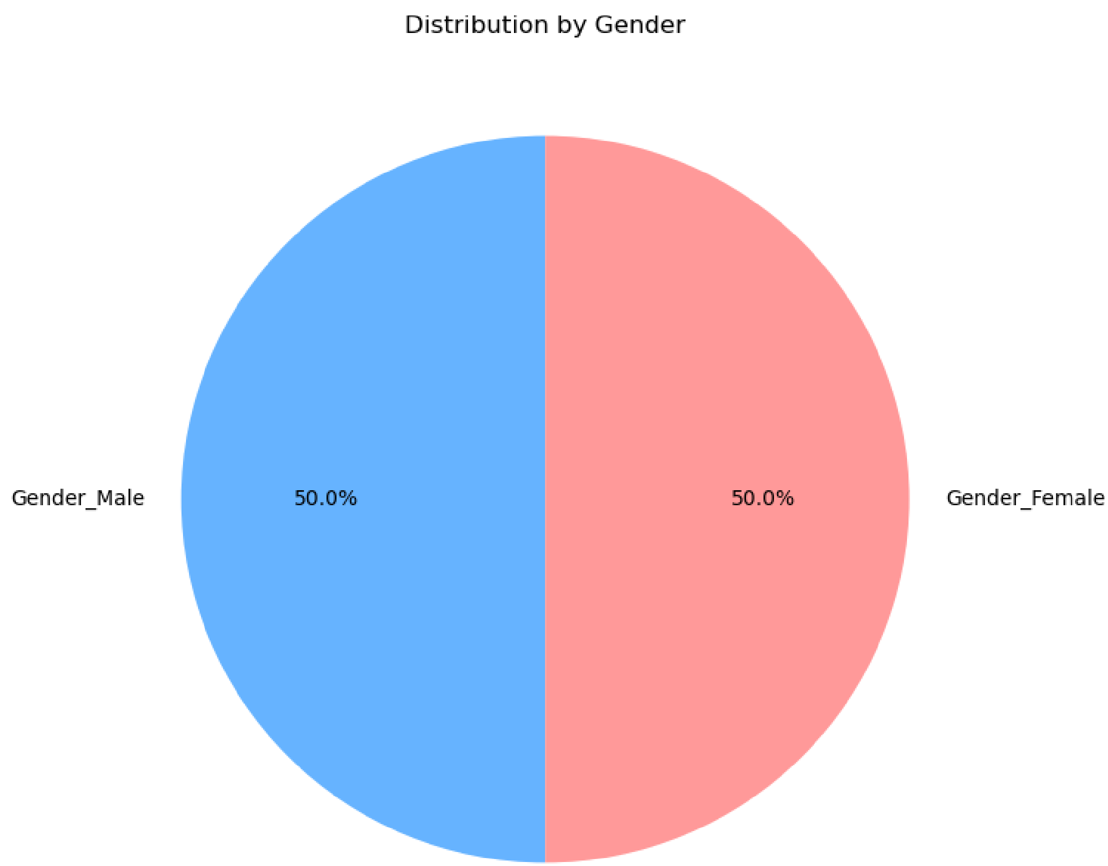




[14]:
```python
# Sum the count of each age group
age_distribution = data.filter(regex='Age_').sum()  # Adjust regex if different␣
↪column naming

# Plotting pie chart for age distribution
plt.figure(figsize=(8, 8))
age_distribution.plot(kind='pie', autopct='%1.1f%%', startangle=90, colors=plt.
↪cm.Paired(np.arange(len(age_distribution))))
plt.title('Distribution by Age Group')
plt.ylabel('')  # Hiding the y-label as it's not necessary for pie charts
plt.show()
```



[15]:
```
# Sum the count of each gender
gender_distribution = data[['Gender_Male', 'Gender_Female']].sum()  # Adjust␣
↪column names as necessary

# Plotting pie chart for gender distribution
plt.figure(figsize=(8, 8))
gender_distribution.plot(kind='pie', autopct='%1.1f%%', startangle=90,␣
↪colors=['#66b3ff', '#ff9999'])
plt.title('Distribution by Gender')
plt.ylabel('')
plt.show()
```



[6]:
```
# Define features and target
X = data.drop('Severity_Mild', axis=1)
y = data['Severity_Mild']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[7]:
```
# Set up a pipeline with SMOTE and a classifier
pipeline_rf = IMBPipeline([
    ('scaler', StandardScaler()),
    ('smote', SMOTE(random_state=42)),
    ('classifier', RandomForestClassifier(random_state=42))
])

# Parameters for GridSearchCV
param_grid_rf = {
```

```
    'classifier__n_estimators': [100, 200],
    'classifier__max_depth': [None, 10, 20]
}

# Grid search with cross-validation
grid_rf = GridSearchCV(pipeline_rf, param_grid_rf, cv=5, scoring='accuracy')
grid_rf.fit(X_train, y_train)
```

[7]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                       ('smote', SMOTE(random_state=42)),
                                       ('classifier',
RandomForestClassifier(random_state=42))]),
             param_grid={'classifier__max_depth': [None, 10, 20],
                         'classifier__n_estimators': [100, 200]},
             scoring='accuracy')
```

[10]:
```
# Predicting and evaluating the model
y_pred_rf = grid_rf.predict(X_test)

print("Best parameters:", grid_rf.best_params_)
print("Accuracy:", accuracy_score(y_test, y_pred_rf))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rf))
print("Classification Report:\n", classification_report(y_test, y_pred_rf))
```

```
Best parameters: {'classifier__max_depth': None, 'classifier__n_estimators':
100}
Accuracy: 0.7519097222222222
Confusion Matrix:
 [[31666 15719]
 [    0 15975]]
Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.67      0.80     47385
           1       0.50      1.00      0.67     15975

    accuracy                           0.75     63360
   macro avg       0.75      0.83      0.74     63360
weighted avg       0.87      0.75      0.77     63360
```

[11]:
```
# Set up a pipeline with SMOTE and Gradient Boosting Classifier
pipeline_gb = IMBPipeline([
    ('scaler', StandardScaler()),
    ('smote', SMOTE(random_state=42)),
    ('classifier', GradientBoostingClassifier(random_state=42))
```

```
])

# Parameters for GridSearchCV
param_grid_gb = {
    'classifier__n_estimators': [100, 150],
    'classifier__learning_rate': [0.1, 0.01],
    'classifier__max_depth': [3, 5]
}

# Grid search with cross-validation
grid_gb = GridSearchCV(pipeline_gb, param_grid_gb, cv=5, scoring='accuracy')
grid_gb.fit(X_train, y_train)

# Predicting and evaluating the model
y_pred_gb = grid_gb.predict(X_test)

print("Best parameters for Gradient Boosting:", grid_gb.best_params_)
print("Accuracy for Gradient Boosting:", accuracy_score(y_test, y_pred_gb))
print("Confusion Matrix for Gradient Boosting:\n", confusion_matrix(y_test,␣
 ↪y_pred_gb))
print("Classification Report for Gradient Boosting:\n",␣
 ↪classification_report(y_test, y_pred_gb))
```

```
Best parameters for Gradient Boosting: {'classifier__learning_rate': 0.1,
'classifier__max_depth': 3, 'classifier__n_estimators': 100}
Accuracy for Gradient Boosting: 0.7519097222222222
Confusion Matrix for Gradient Boosting:
 [[31666 15719]
 [    0 15975]]
Classification Report for Gradient Boosting:
              precision    recall  f1-score   support

           0       1.00      0.67      0.80     47385
           1       0.50      1.00      0.67     15975

    accuracy                           0.75     63360
   macro avg       0.75      0.83      0.74     63360
weighted avg       0.87      0.75      0.77     63360
```

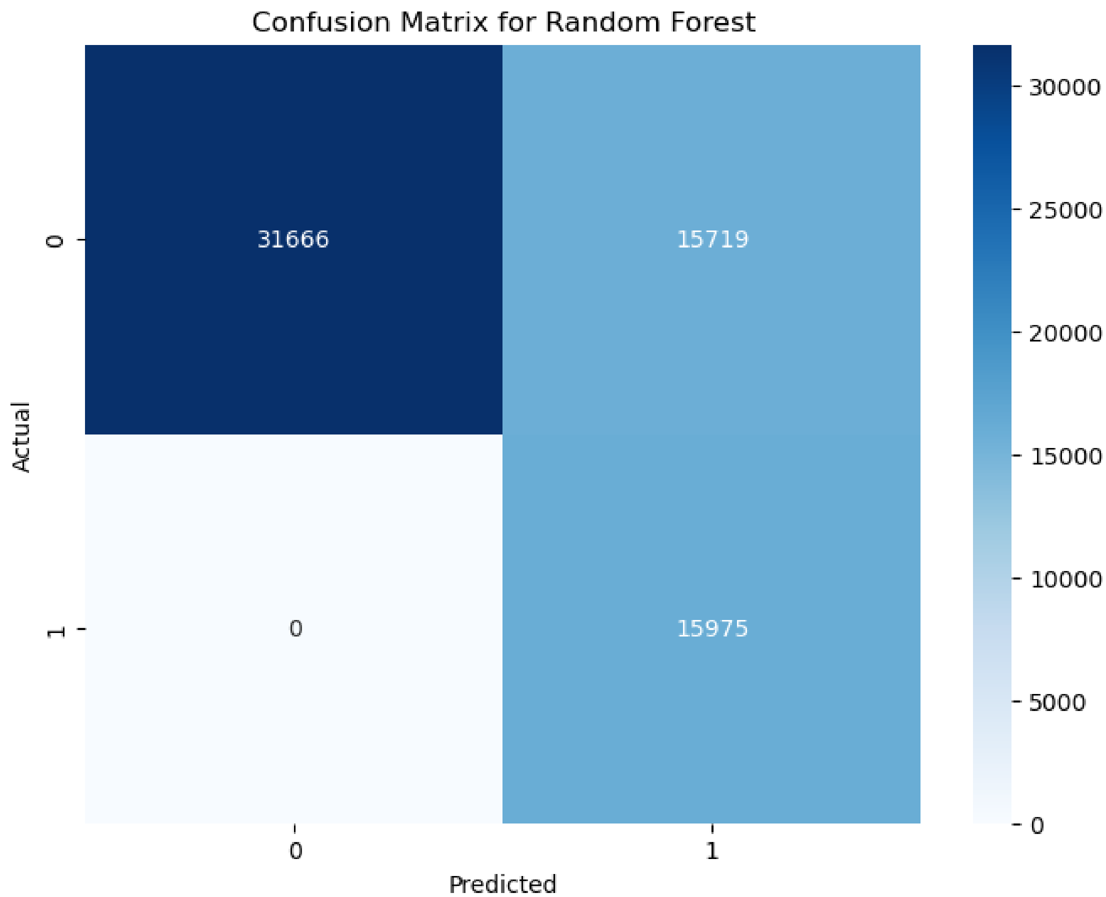
[13]:
```
# Set up a pipeline with SMOTE and K-Nearest Neighbors Classifier
pipeline_knn = IMBPipeline([
    ('scaler', StandardScaler()),
    ('smote', SMOTE(random_state=42)),
    ('classifier', KNeighborsClassifier())
])
```

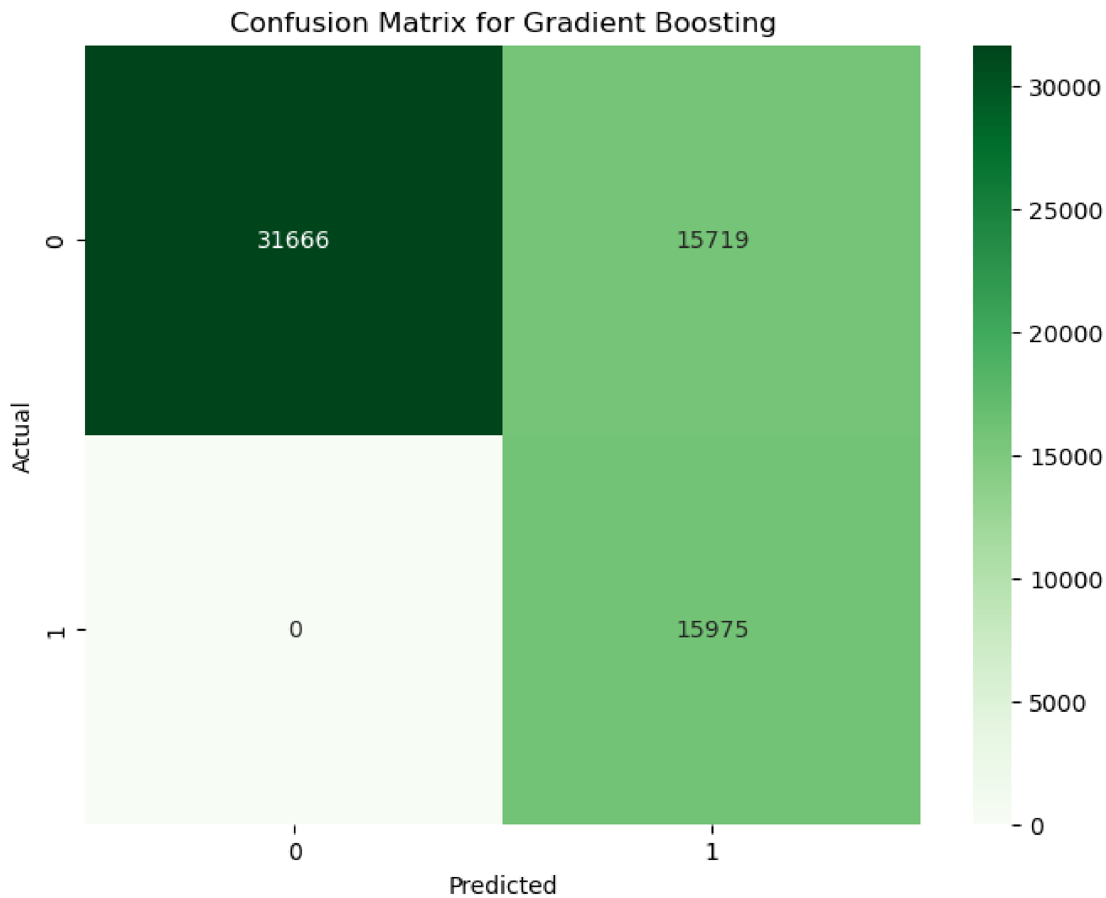
```
# Parameters for GridSearchCV
param_grid_knn = {
    'classifier__n_neighbors': [3, 5, 7],
    'classifier__weights': ['uniform', 'distance']
}

# Grid search with cross-validation
grid_knn = GridSearchCV(pipeline_knn, param_grid_knn, cv=5, scoring='accuracy')
grid_knn.fit(X_train, y_train)

# Predicting and evaluating the model
y_pred_knn = grid_knn.predict(X_test)

print("Best parameters for KNN:", grid_knn.best_params_)
print("Accuracy for KNN:", accuracy_score(y_test, y_pred_knn))
print("Confusion Matrix for KNN:\n", confusion_matrix(y_test, y_pred_knn))
print("Classification Report for KNN:\n", classification_report(y_test,␣
↪y_pred_knn))
```

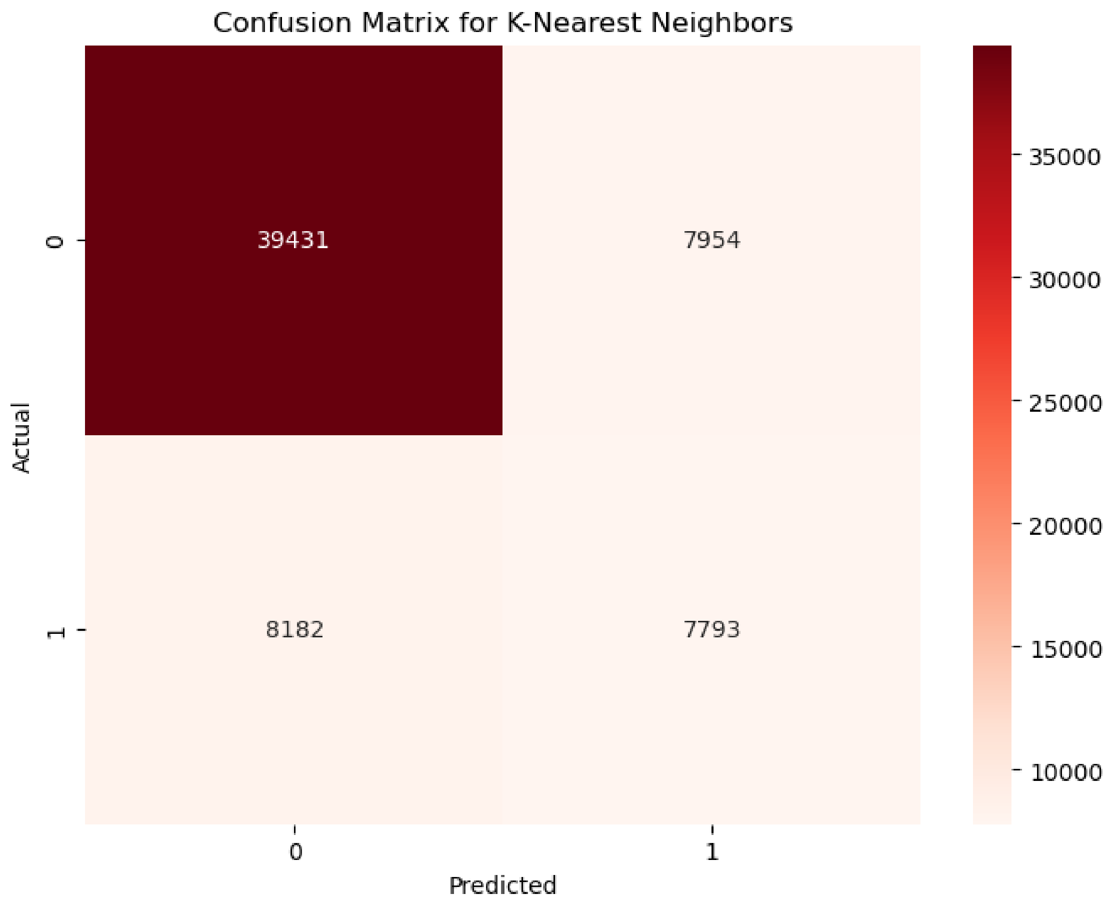
```
Best parameters for KNN: {'classifier__n_neighbors': 3, 'classifier__weights':
'uniform'}
Accuracy for KNN: 0.7453282828282828
Confusion Matrix for KNN:
 [[39431  7954]
 [ 8182  7793]]
Classification Report for KNN:
               precision    recall  f1-score   support

           0       0.83      0.83      0.83     47385
           1       0.49      0.49      0.49     15975

    accuracy                           0.75     63360
   macro avg       0.66      0.66      0.66     63360
weighted avg       0.74      0.75      0.74     63360
```

[18]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Confusion matrix for Random Forest
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_rf, annot=True, fmt="d", cmap="Blues")
plt.title("Confusion Matrix for Random Forest")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
# Confusion matrix for Gradient Boosting
conf_matrix_gb = confusion_matrix(y_test, y_pred_gb)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_gb, annot=True, fmt="d", cmap="Greens")
plt.title("Confusion Matrix for Gradient Boosting")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# Confusion matrix for K-Nearest Neighbors
conf_matrix_knn = confusion_matrix(y_test, y_pred_knn)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_knn, annot=True, fmt="d", cmap="Reds")
plt.title("Confusion Matrix for K-Nearest Neighbors")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```




Confusion Matrix for Gradient Boosting
31666
15719
0
15975
Actual
Predicted
0
1
0
1
30000
25000
20000
15000
10000
5000
0


Confusion Matrix for K-Nearest Neighbors
39431
7954
8182
7793
Actual
0
1
Predicted
0
1
35000
30000
25000
20000
15000
10000

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