Autism Prediction

December 6, 2024

[3]:
```
# Importing necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from imblearn.over_sampling import SMOTE
import warnings
warnings.filterwarnings("ignore")
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪RandomizedSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,␣
↪classification_report
import pickle
```

[16]:
```
#loading the dataset
df = pd.read_csv(r'C:\Users\PC\Desktop\Datasets\Autism.csv')
```

[5]:
```
#viewing the first five entries
df.head()
```

[5]:
```
   ID  A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  A6_Score  A7_Score  \
0   1         1         0         1         0         1         0         1
1   2         0         0         0         0         0         0         0
2   3         1         1         1         1         1         1         1
3   4         0         0         0         0         0         0         0
4   5         0         0         0         0         0         0         0

   A8_Score  A9_Score  …  gender       ethnicity jaundice austim  \
0         0         1  …       f               ?       no     no
1         0         0  …       m               ?       no     no
2         1         1  …       m  White-European       no    yes
3         0         0  …       f               ?       no     no
4         0         0  …       m               ?       no     no
```

```
   contry_of_res used_app_before     result     age_desc  relation Class/ASD
0        Austria              no   6.351166  18 and more      Self         0
1          India              no   2.255185  18 and more      Self         0
2  United States              no  14.851484  18 and more      Self         1
3  United States              no   2.276617  18 and more      Self         0
4   South Africa              no  -4.777286  18 and more      Self         0

[5 rows x 22 columns]
```

Observation - The dataset contains diverse variables, with the gender column reflecting gender distribution, ethnicity showing some missing data, country_of_res indicating geographical diversity, result representing autism screening scores, age_desc implying adult participants, and Class/ASD denoting autism diagnosis.

[17]:
```
df.tail()
```

[17]:
```
      ID  A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  A6_Score  \
795  796         0         1         0         0         0         0
796  797         0         1         1         0         0         1
797  798         0         0         0         0         0         0
798  799         0         0         0         0         0         0
799  800         0         1         0         0         0         0

     A7_Score  A8_Score  A9_Score  A10_Score        age gender  \
795         0         0         1          1  16.597187      m
796         0         1         1          1  20.703001      m
797         0         0         0          0   5.711481      m
798         0         0         0          0  16.414305      f
799         0         0         0          0  46.966113      f

          ethnicity jaundice austim         contry_of_res used_app_before  \
795        Hispanic       no     no           New Zealand              no
796  White-European       no     no                Cyprus              no
797     South Asian      yes     no           New Zealand              no
798               ?       no     no                Canada              no
799               ?       no     no  United Arab Emirates             yes

        result     age_desc relation  Class/ASD
795  12.999501  18 and more     Self          0
796  13.561518  18 and more     Self          0
797   2.653177  18 and more     Self          0
798   9.069342  18 and more     Self          0
799   2.243304  18 and more     Self          0
```

[18]:
```
df.shape
```

[18]: (800, 22)

Observation - The dataset, with a shape of (800, 22), indicates it consists of 800 rows and 22 columns, representing various attributes related to autism screening and diagnosis across a diverse population.

[9]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 800 entries, 0 to 799
Data columns (total 22 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ID               800 non-null    int64
 1   A1_Score         800 non-null    int64
 2   A2_Score         800 non-null    int64
 3   A3_Score         800 non-null    int64
 4   A4_Score         800 non-null    int64
 5   A5_Score         800 non-null    int64
 6   A6_Score         800 non-null    int64
 7   A7_Score         800 non-null    int64
 8   A8_Score         800 non-null    int64
 9   A9_Score         800 non-null    int64
 10  A10_Score        800 non-null    int64
 11  age              800 non-null    float64
 12  gender           800 non-null    object
 13  ethnicity        800 non-null    object
 14  jaundice         800 non-null    object
 15  austim           800 non-null    object
 16  contry_of_res    800 non-null    object
 17  used_app_before  800 non-null    object
 18  result           800 non-null    float64
 19  age_desc         800 non-null    object
 20  relation         800 non-null    object
 21  Class/ASD        800 non-null    int64
dtypes: float64(2), int64(12), object(8)
memory usage: 137.6+ KB
```

[19]:
```python
# convert age column datatype to integer
df["age"] = df["age"].astype(int)
```

[20]:
```python
#Identifying and printing the unique values of non-numerical columns in a df,␣
↪excluding specified columns like "ID", "age", and "result".
for col in df.columns:
  numerical_features = ["ID", "age", "result"]
  if col not in numerical_features:
    print(col, df[col].unique())
    print("-"*50)
```

```
A1_Score [1 0]
--------------------------------------------------
A2_Score [0 1]
```

```
--------------------------------------------------
A3_Score [1 0]
--------------------------------------------------
A4_Score [0 1]
--------------------------------------------------
A5_Score [1 0]
--------------------------------------------------
A6_Score [0 1]
--------------------------------------------------
A7_Score [1 0]
--------------------------------------------------
A8_Score [0 1]
--------------------------------------------------
A9_Score [1 0]
--------------------------------------------------
A10_Score [1 0]
--------------------------------------------------
gender ['f' 'm']
--------------------------------------------------
ethnicity ['?' 'White-European' 'Middle Eastern ' 'Pasifika' 'Black' 'Others'
 'Hispanic' 'Asian' 'Turkish' 'South Asian' 'Latino' 'others']
--------------------------------------------------
jaundice ['no' 'yes']
--------------------------------------------------
austim ['no' 'yes']
--------------------------------------------------
contry_of_res ['Austria' 'India' 'United States' 'South Africa' 'Jordan'
 'United Kingdom' 'Brazil' 'New Zealand' 'Canada' 'Kazakhstan'
 'United Arab Emirates' 'Australia' 'Ukraine' 'Iraq' 'France' 'Malaysia'
 'Viet Nam' 'Egypt' 'Netherlands' 'Afghanistan' 'Oman' 'Italy'
 'AmericanSamoa' 'Bahamas' 'Saudi Arabia' 'Ireland' 'Aruba' 'Sri Lanka'
 'Russia' 'Bolivia' 'Azerbaijan' 'Armenia' 'Serbia' 'Ethiopia' 'Sweden'
 'Iceland' 'Hong Kong' 'Angola' 'China' 'Germany' 'Spain' 'Tonga'
 'Pakistan' 'Iran' 'Argentina' 'Japan' 'Mexico' 'Nicaragua' 'Sierra Leone'
 'Czech Republic' 'Niger' 'Romania' 'Cyprus' 'Belgium' 'Burundi'
 'Bangladesh']
--------------------------------------------------
used_app_before ['no' 'yes']
--------------------------------------------------
age_desc ['18 and more']
--------------------------------------------------
relation ['Self' 'Relative' 'Parent' '?' 'Others' 'Health care professional']
--------------------------------------------------
Class/ASD [0 1]
--------------------------------------------------
```

[21]:
```
# dropping ID & age_desc column
df = df.drop(columns=["ID", "age_desc"])
df.columns
```

[21]:
```
Index(['A1_Score', 'A2_Score', 'A3_Score', 'A4_Score', 'A5_Score', 'A6_Score',
       'A7_Score', 'A8_Score', 'A9_Score', 'A10_Score', 'age', 'gender',
       'ethnicity', 'jaundice', 'austim', 'contry_of_res', 'used_app_before',
       'result', 'relation', 'Class/ASD'],
      dtype='object')
```

[22]:
```
df["contry_of_res"].unique()
```

[22]:
```
array(['Austria', 'India', 'United States', 'South Africa', 'Jordan',
       'United Kingdom', 'Brazil', 'New Zealand', 'Canada', 'Kazakhstan',
       'United Arab Emirates', 'Australia', 'Ukraine', 'Iraq', 'France',
       'Malaysia', 'Viet Nam', 'Egypt', 'Netherlands', 'Afghanistan',
       'Oman', 'Italy', 'AmericanSamoa', 'Bahamas', 'Saudi Arabia',
       'Ireland', 'Aruba', 'Sri Lanka', 'Russia', 'Bolivia', 'Azerbaijan',
       'Armenia', 'Serbia', 'Ethiopia', 'Sweden', 'Iceland', 'Hong Kong',
       'Angola', 'China', 'Germany', 'Spain', 'Tonga', 'Pakistan', 'Iran',
       'Argentina', 'Japan', 'Mexico', 'Nicaragua', 'Sierra Leone',
       'Czech Republic', 'Niger', 'Romania', 'Cyprus', 'Belgium',
       'Burundi', 'Bangladesh'], dtype=object)
```

[23]:
```
# Standardize country names in the 'contry_of_res' column using the mapping␣
↪dictionary
# define the mapping dictionary for country names
mapping = {
    "Viet Nam": "Vietnam",
    "AmericanSamoa": "United States",
    "Hong Kong": "China"
}

# repalce value in the country column
df["contry_of_res"] = df["contry_of_res"].replace(mapping)
```

[24]:
```
df["contry_of_res"].unique()
```

[24]:
```
array(['Austria', 'India', 'United States', 'South Africa', 'Jordan',
       'United Kingdom', 'Brazil', 'New Zealand', 'Canada', 'Kazakhstan',
       'United Arab Emirates', 'Australia', 'Ukraine', 'Iraq', 'France',
       'Malaysia', 'Vietnam', 'Egypt', 'Netherlands', 'Afghanistan',
       'Oman', 'Italy', 'Bahamas', 'Saudi Arabia', 'Ireland', 'Aruba',
       'Sri Lanka', 'Russia', 'Bolivia', 'Azerbaijan', 'Armenia',
       'Serbia', 'Ethiopia', 'Sweden', 'Iceland', 'China', 'Angola',
       'Germany', 'Spain', 'Tonga', 'Pakistan', 'Iran', 'Argentina',
       'Japan', 'Mexico', 'Nicaragua', 'Sierra Leone', 'Czech Republic',
```

```
 'Niger', 'Romania', 'Cyprus', 'Belgium', 'Burundi', 'Bangladesh'],
dtype=object)
```

The code standardizes country names in a DataFrame column using a mapping dictionary to ensure consistent data.

[25]:
```
# taget class distribution
df["Class/ASD"].value_counts()
```

[25]:
```
Class/ASD
0    639
1    161
Name: count, dtype: int64
```

Observations - Identified class imbalance 639 (Class 0) vs. 161 (Class 1) - Dropped ID and age_desc; standardized contry_of_res using a mapping - Missing values in ethnicity & relation

Exploratory Data Analysis

[27]:
```
df.describe()
```

[27]:
```
        A1_Score    A2_Score    A3_Score   A4_Score    A5_Score    A6_Score  \
count 800.000000  800.000000  800.000000  800.00000  800.000000  800.000000
mean    0.560000    0.530000    0.450000    0.41500    0.395000    0.303750
std     0.496697    0.499411    0.497805    0.49303    0.489157    0.460164
min     0.000000    0.000000    0.000000    0.00000    0.000000    0.000000
25%     0.000000    0.000000    0.000000    0.00000    0.000000    0.000000
50%     1.000000    1.000000    0.000000    0.00000    0.000000    0.000000
75%     1.000000    1.000000    1.000000    1.00000    1.000000    1.000000
max     1.000000    1.000000    1.000000    1.00000    1.000000    1.000000

        A7_Score    A8_Score    A9_Score   A10_Score         age      result  \
count 800.000000  800.000000  800.000000  800.000000  800.000000  800.000000
mean    0.397500    0.508750    0.495000    0.617500   27.963750    8.537303
std     0.489687    0.500236    0.500288    0.486302   16.329827    4.807676
min     0.000000    0.000000    0.000000    0.000000    2.000000   -6.137748
25%     0.000000    0.000000    0.000000    0.000000   17.000000    5.306575
50%     0.000000    1.000000    0.000000    1.000000   24.000000    9.605299
75%     1.000000    1.000000    1.000000    1.000000   35.250000   12.514484
max     1.000000    1.000000    1.000000    1.000000   89.000000   15.853126

       Class/ASD
count 800.000000
mean    0.201250
std     0.401185
min     0.000000
25%     0.000000
50%     0.000000
75%     0.000000
```

```
max      1.000000
```

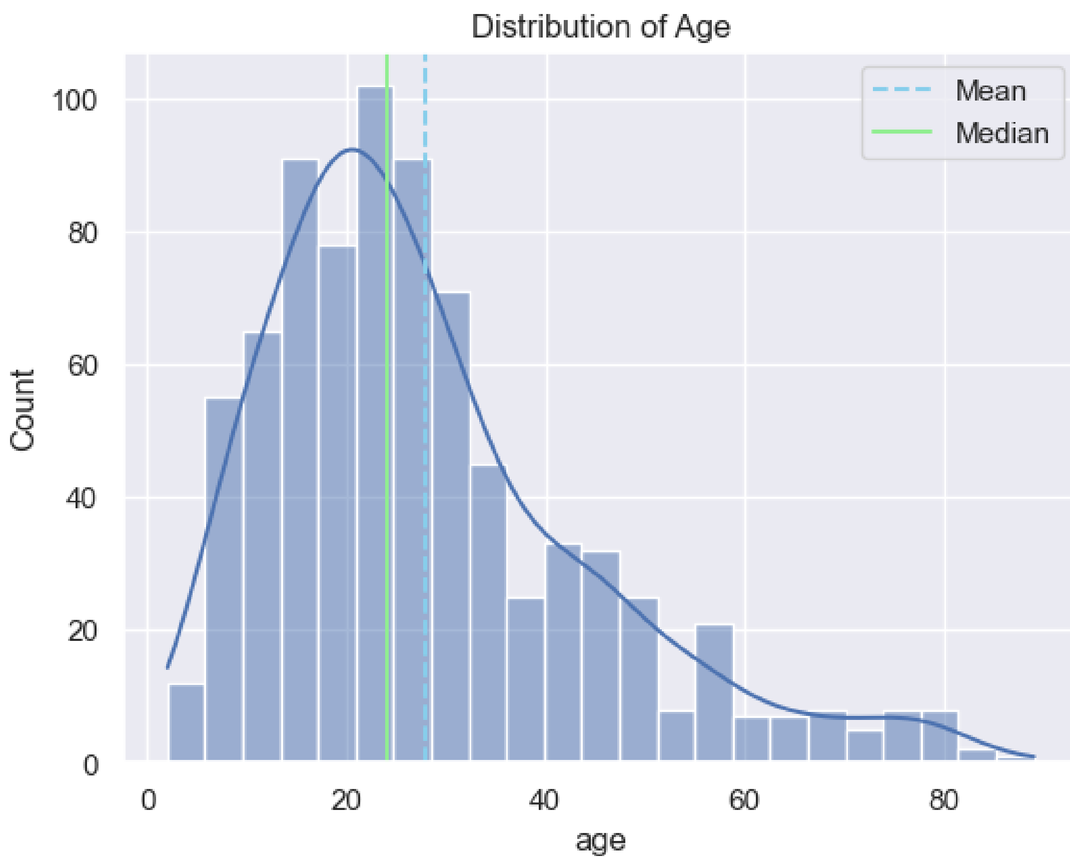
Observations - A1 to A10 Scores: Binary values (0 or 1). - Mean Scores: Range from 0.304 (A6) to 0.618 (A10). - Median Values: Most scores have a median of 0, except A1, A2, A8, A9, and A10, which have a median of 1. - Distribution: Some scores are almost evenly split between 0 and 1, while others lean more towards 0 or 1.

The scores are mostly binary with varying means and distributions, indicating different tendencies towards 0 or 1 across the scores.

[28]:

```python
# Histogram for "age"
sns.set_theme(style="darkgrid")

sns.histplot(df["age"], kde=True)
plt.title("Distribution of Age")

# calculate mean and median
age_mean = df["age"].mean()
age_median = df["age"].median()

print("Mean:", age_mean)
print("Median:", age_median)


# add vertical lines for mean and median
plt.axvline(age_mean, color="skyblue", linestyle="--", label="Mean")
plt.axvline(age_median, color="lightgreen", linestyle="-", label="Median")

plt.legend()

plt.show()
```

```
Mean: 27.96375
Median: 24.0
```

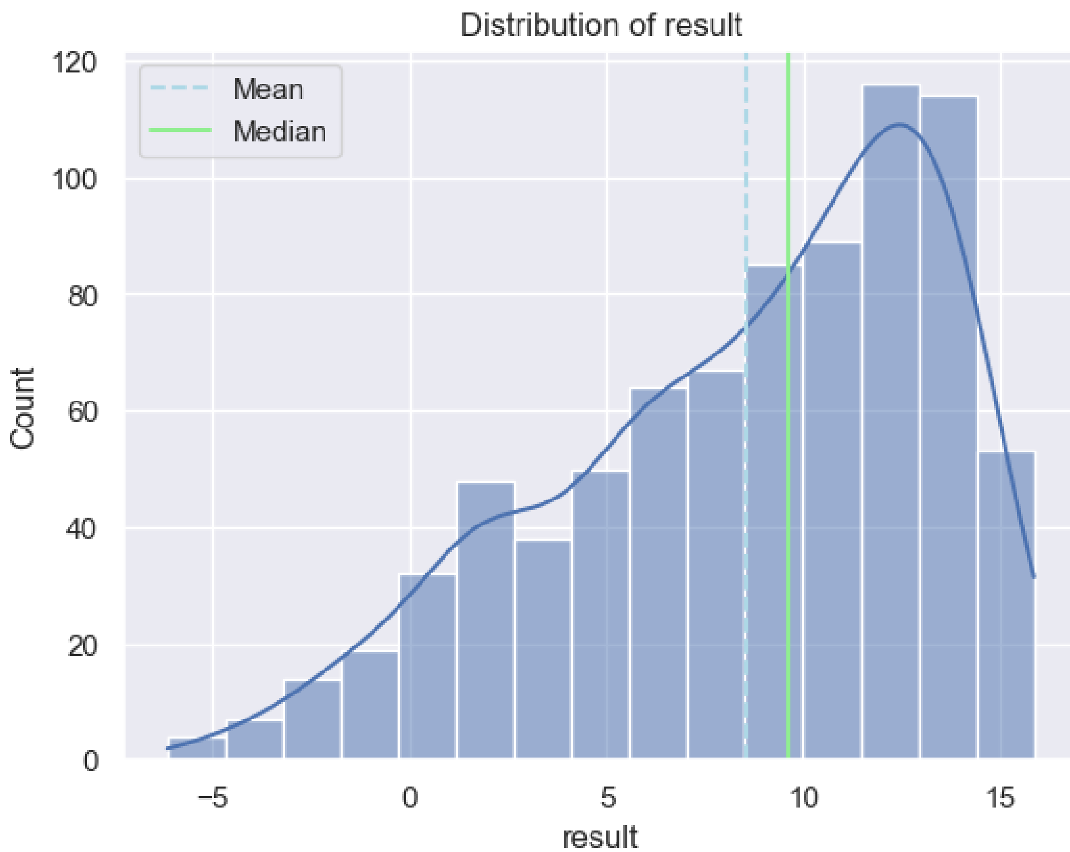


Observation - The plot is left-skewed, indicating a concentration of values toward the higher end, and the mean is less than the median. - The presence of outliers or a clustered data range could be contributing to the skewness, requiring further investigation or potential transformation to normalize the distribution.

[29]:
```
# Histogram for "result"

sns.histplot(df["result"], kde=True)
plt.title("Distribution of result")

# calculate mean and median
result_mean = df["result"].mean()
result_median = df["result"].median()

print("Mean:", result_mean)
print("Median:", result_median)


# add vertical lines for mean and median
plt.axvline(result_mean, color="lightblue", linestyle="--", label="Mean")
```

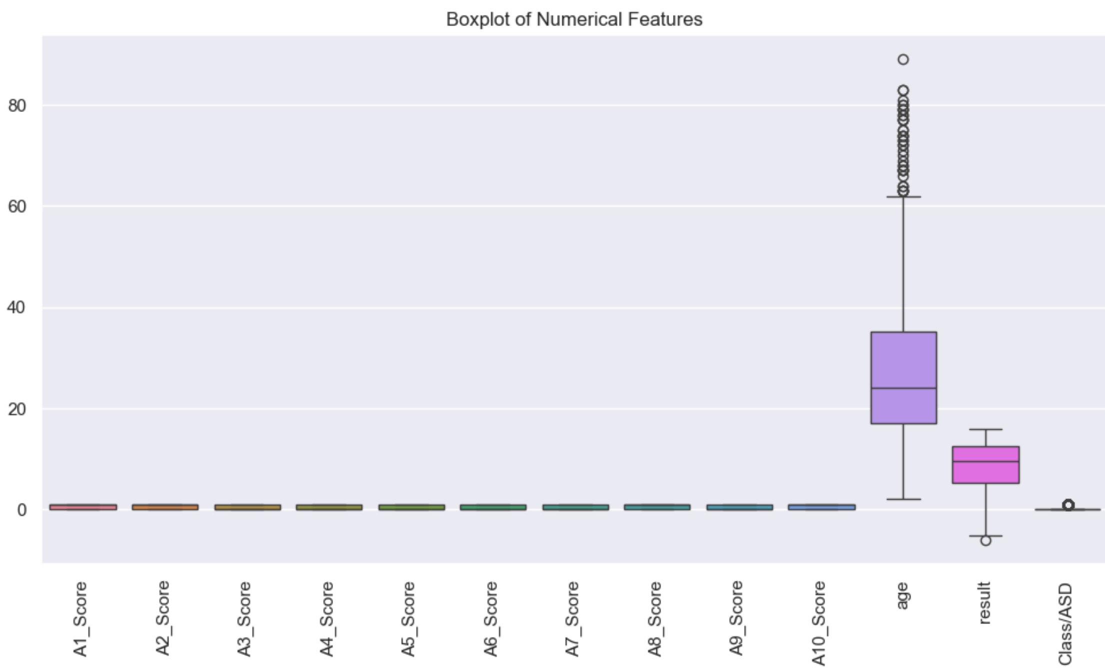
```
plt.axvline(result_median, color="lightgreen", linestyle="-", label="Median")

plt.legend()

plt.show()
```

```
Mean: 8.537303106501248
Median: 9.605299308
```



Observation - The plot is right-skewed, indicating a concentration of values toward the lower end, with the mean being higher than the median. This suggests a positively skewed distribution, The presence of outliers or a clustered data range could be contributing to the skewness, requiring further investigation.

[33]:
```
#Box plot visualization
plt.figure(figsize=(12, 6))
sns.boxplot(data=df)
plt.title('Boxplot of Numerical Features')
plt.xticks(rotation=90)  # Rotate x-axis labels for better readability
plt.show()
```



Observation - The box plot reveals significant variability in age and some outliers in scores and results, while the Class/ASD feature shows less spread.

[34]:
```python
# Identify outliers in the 'age' column using the IQR method (1.5 * IQR rule)
Q1 = df["age"].quantile(0.25)
Q3 = df["age"].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
age_outliers = df[(df["age"] < lower_bound) | (df["age"] > upper_bound)]

len(age_outliers)
```

[34]: 39

[38]:
```python
# Outliers Replacement in Age Column
median_value = df['age'].median()
df.loc[(df['age'] < lower_bound) | (df['age'] > upper_bound), 'age'] =␣
 ↪median_value
```

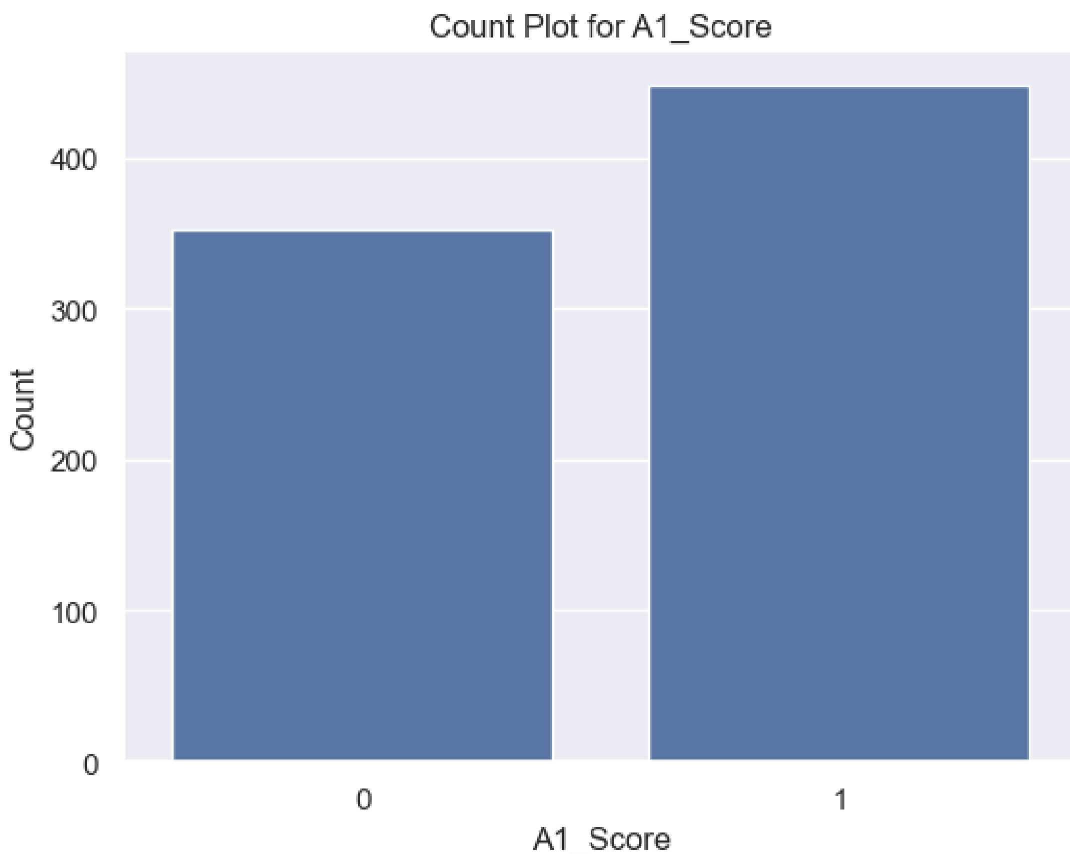
[39]:
```python
# Identify outliers in the 'Result' column using the IQR method (1.5 * IQR rule)
Q1 = df["result"].quantile(0.25)
Q3 = df["result"].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
```

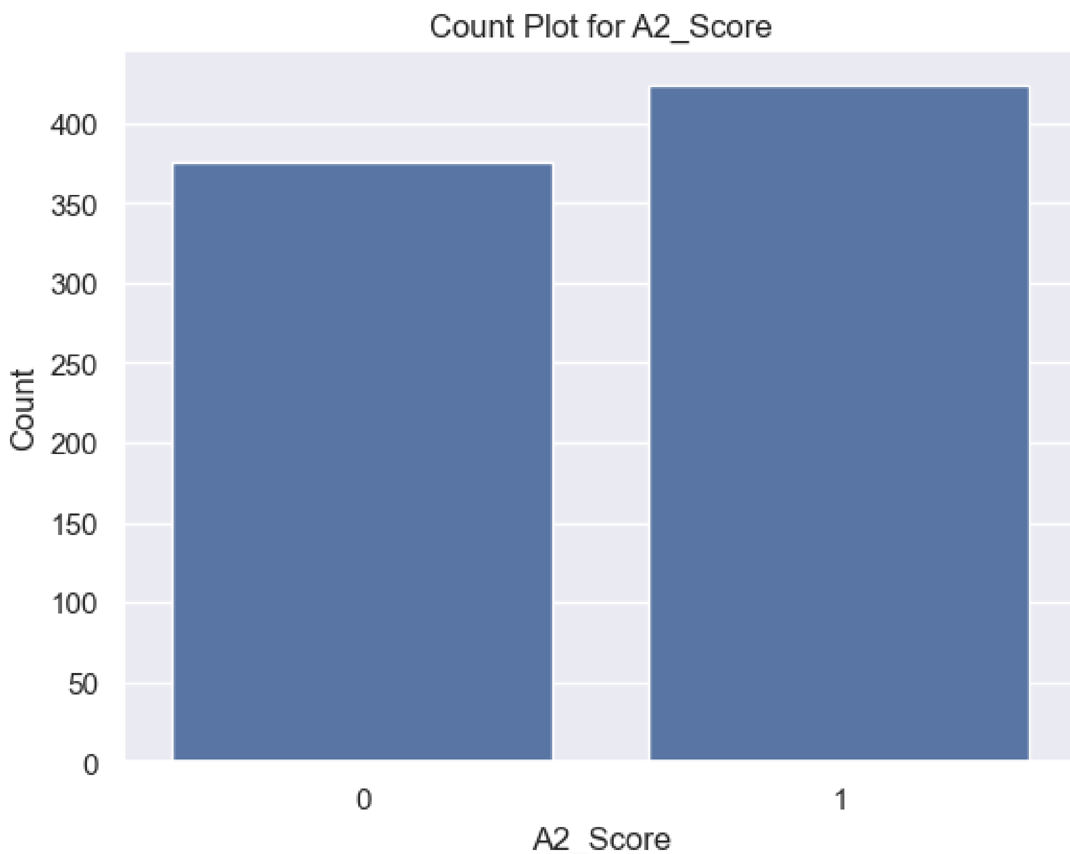
```
result_outliers = df[(df["result"] < lower_bound) | (df["result"] >␣
↪upper_bound)]

len(result_outliers)
```

[39]: 1

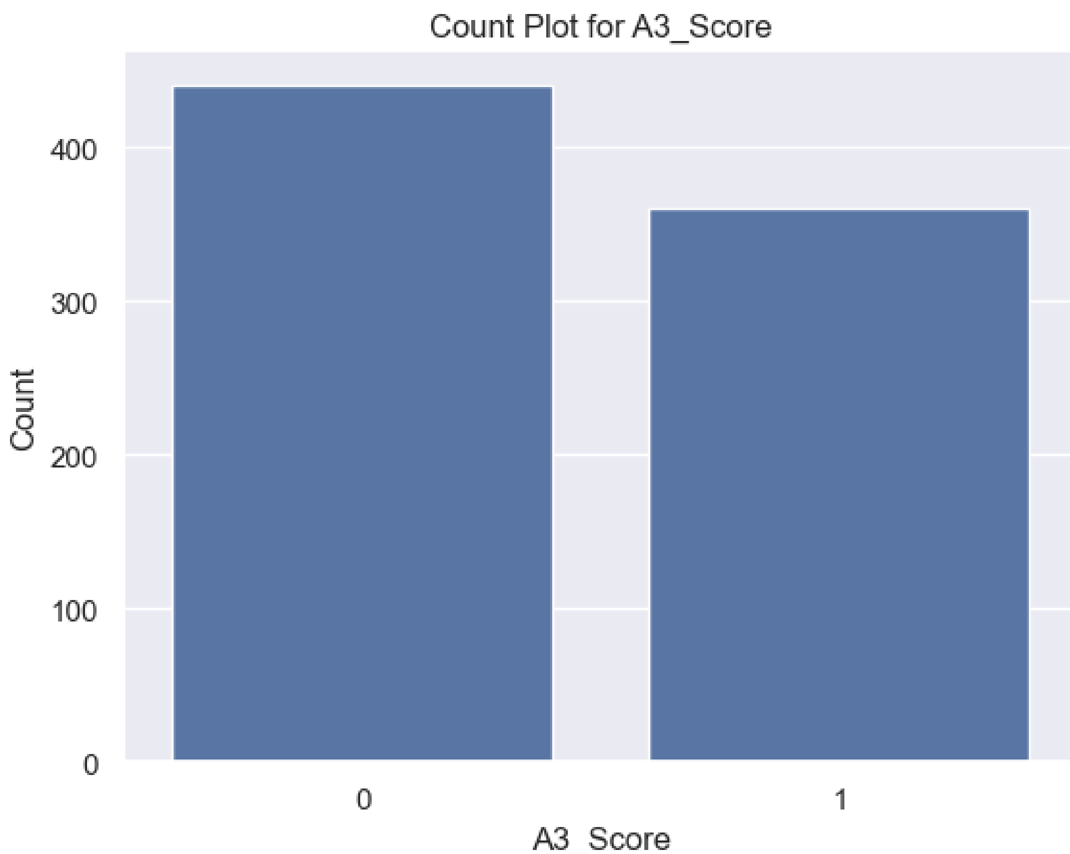
[54]:
```
# Outliers Replacement in Age Column
median_value = df['result'].median()
df.loc[(df['result'] < lower_bound) | (df['result'] > upper_bound), 'result'] =␣
↪median_value
```

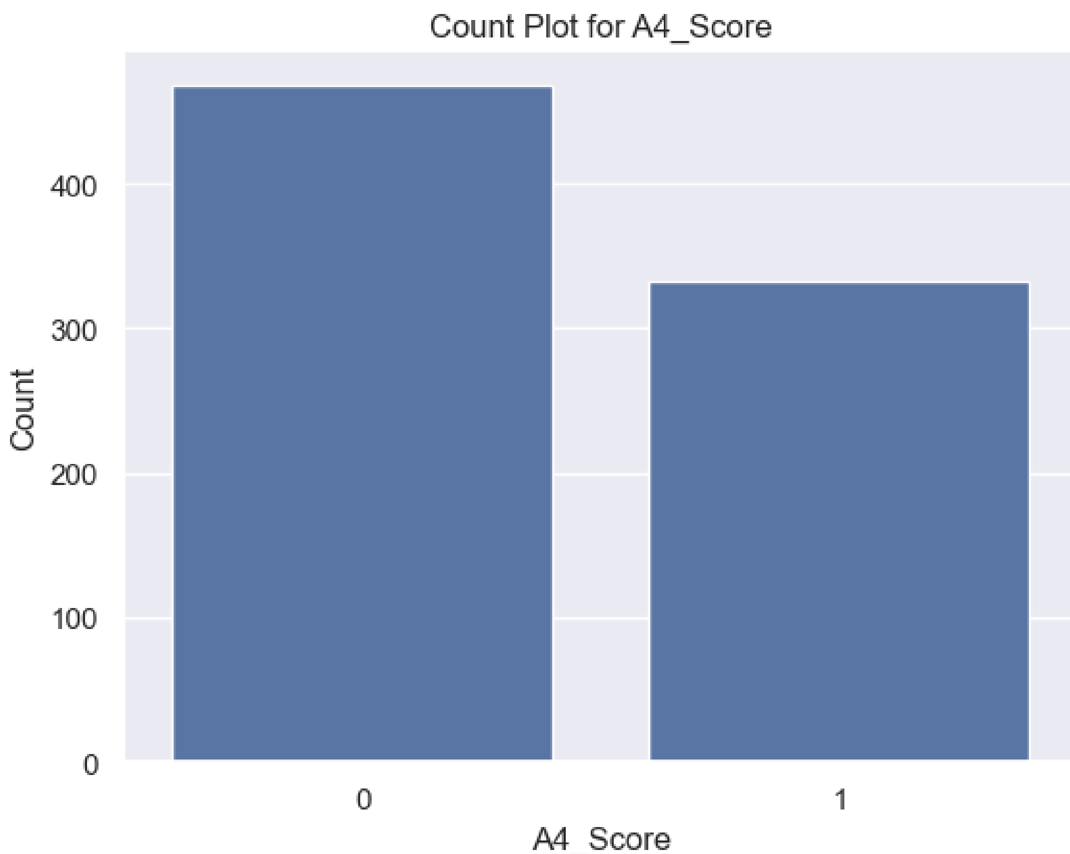
[41]:
```
categorical_columns = ['A1_Score', 'A2_Score', 'A3_Score', 'A4_Score',␣
↪'A5_Score', 'A6_Score',
       'A7_Score', 'A8_Score', 'A9_Score', 'A10_Score', 'gender',
       'ethnicity', 'jaundice', 'austim', 'contry_of_res', 'used_app_before',
       'relation']

for col in categorical_columns:
  sns.countplot(x=df[col])
  plt.title(f"Count Plot for {col}")
  plt.xlabel(col)
  plt.ylabel("Count")
  plt.show()
```


Count Plot for A1_Score
Count
400
300
200
100
0
0
1
A1_Score

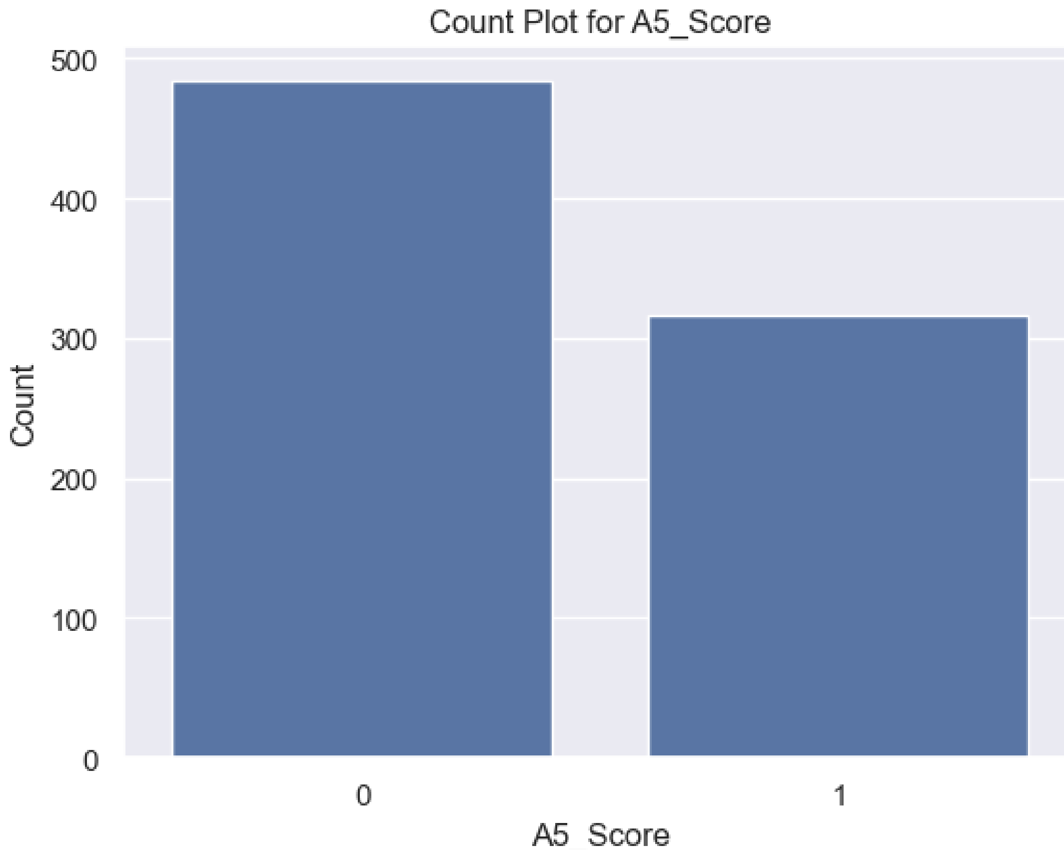


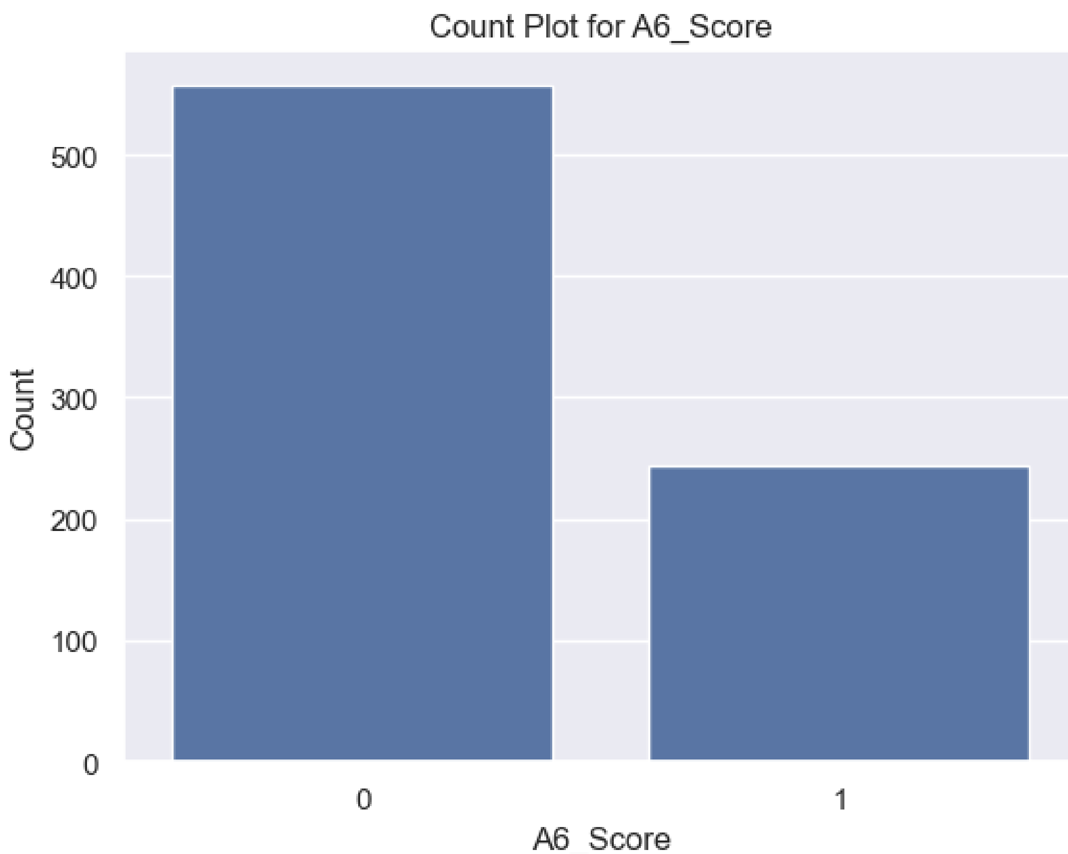
Count Plot for A2_Score
Count
400
350
300
250
200
150
100
50
0
0
1
A2_Score

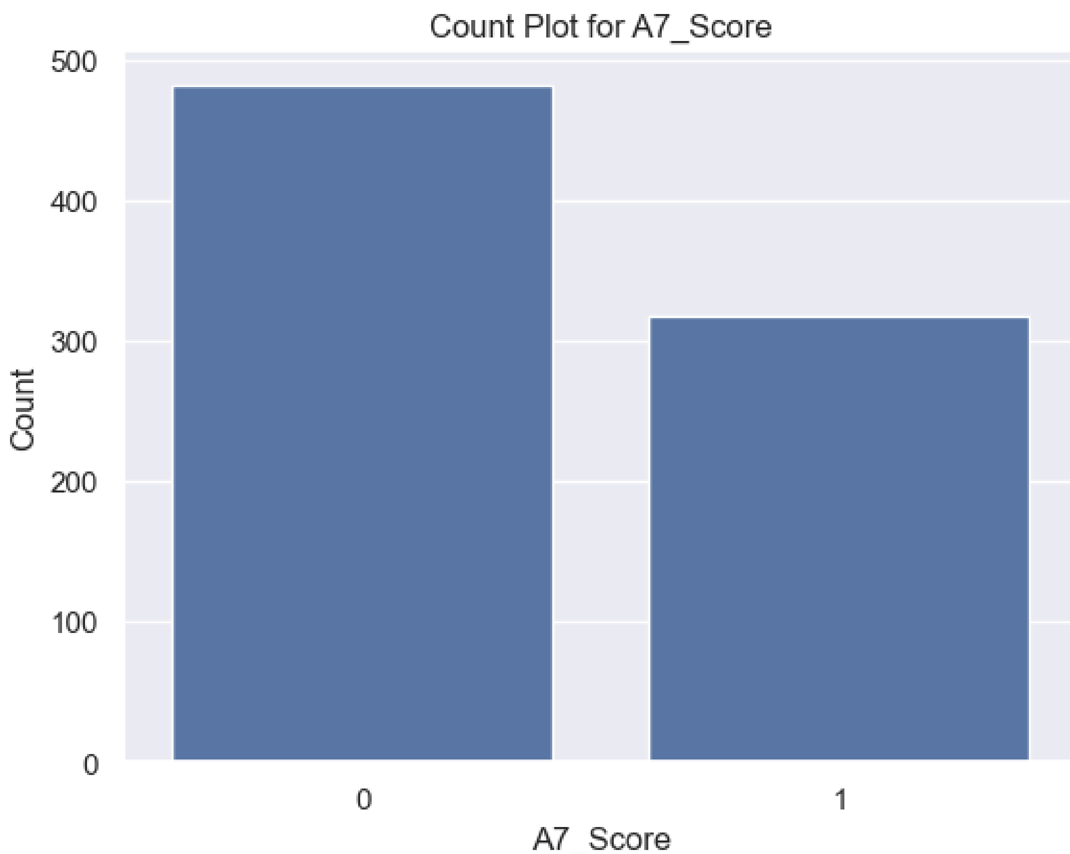

Count Plot for A3_Score
Count
400
300
200
100
0
0
1
A3_Score

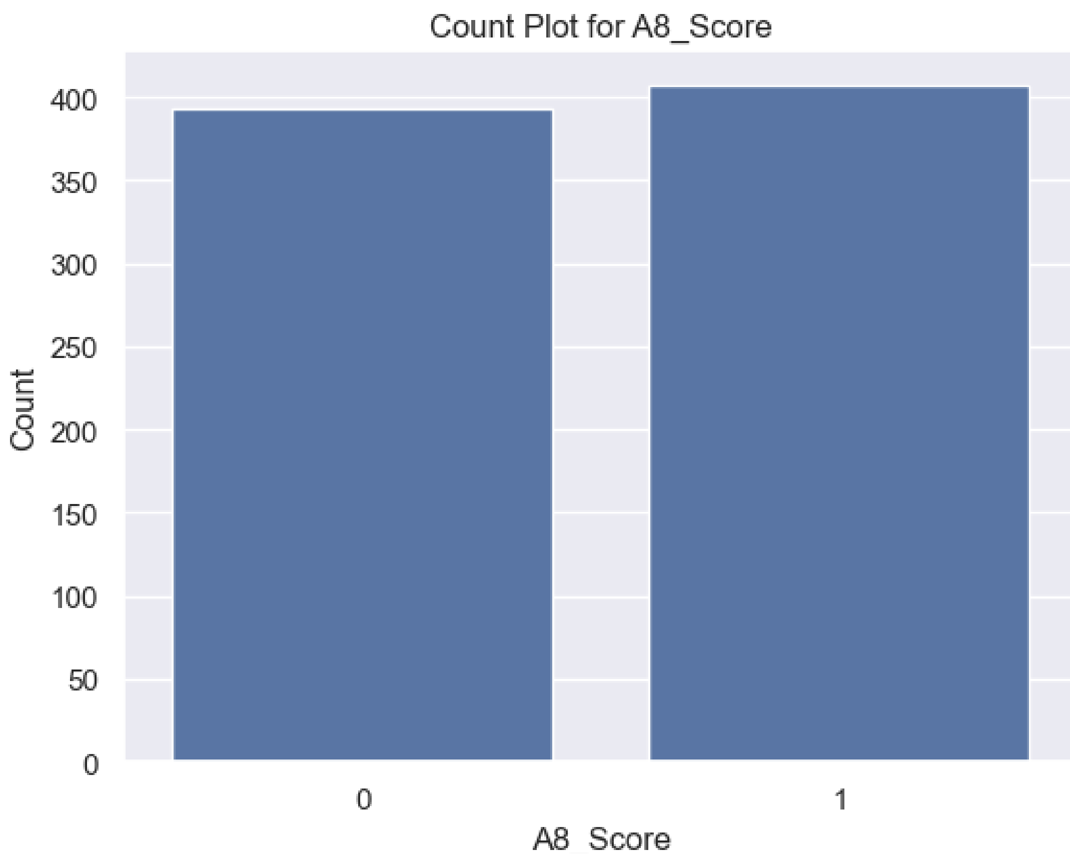


Count Plot for A4_Score
400
300
200
100
0
Count
0
1
A4_Score

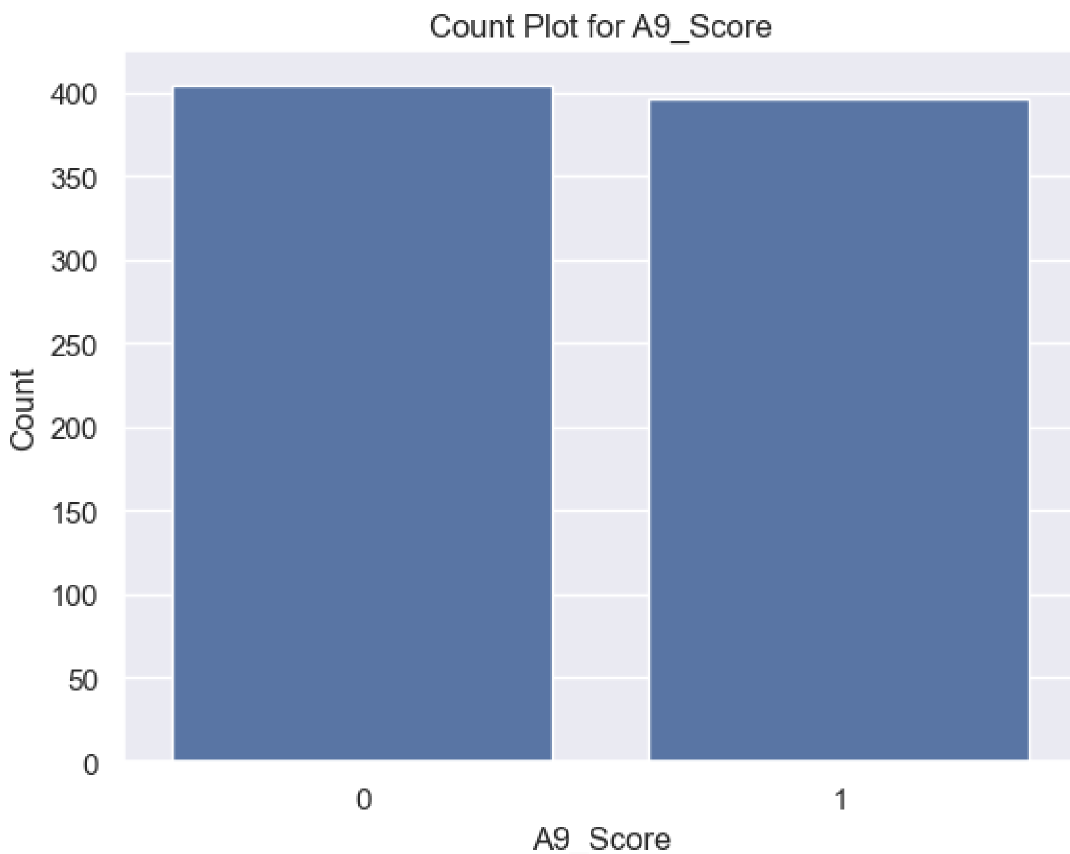

Count Plot for A5_Score
500
400
300
200
100
0
Count
0
1
A5_Score

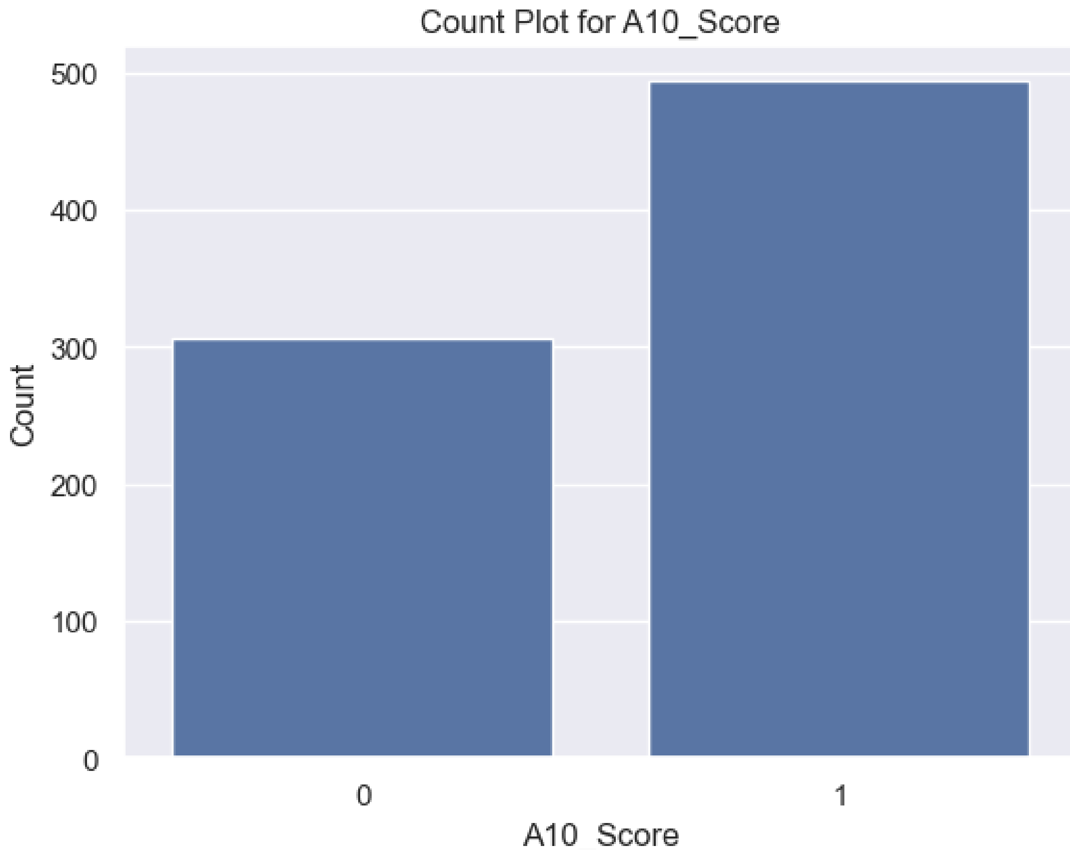

Count Plot for A6_Score
Count
500
400
300
200
100
0
0
1
A6_Score

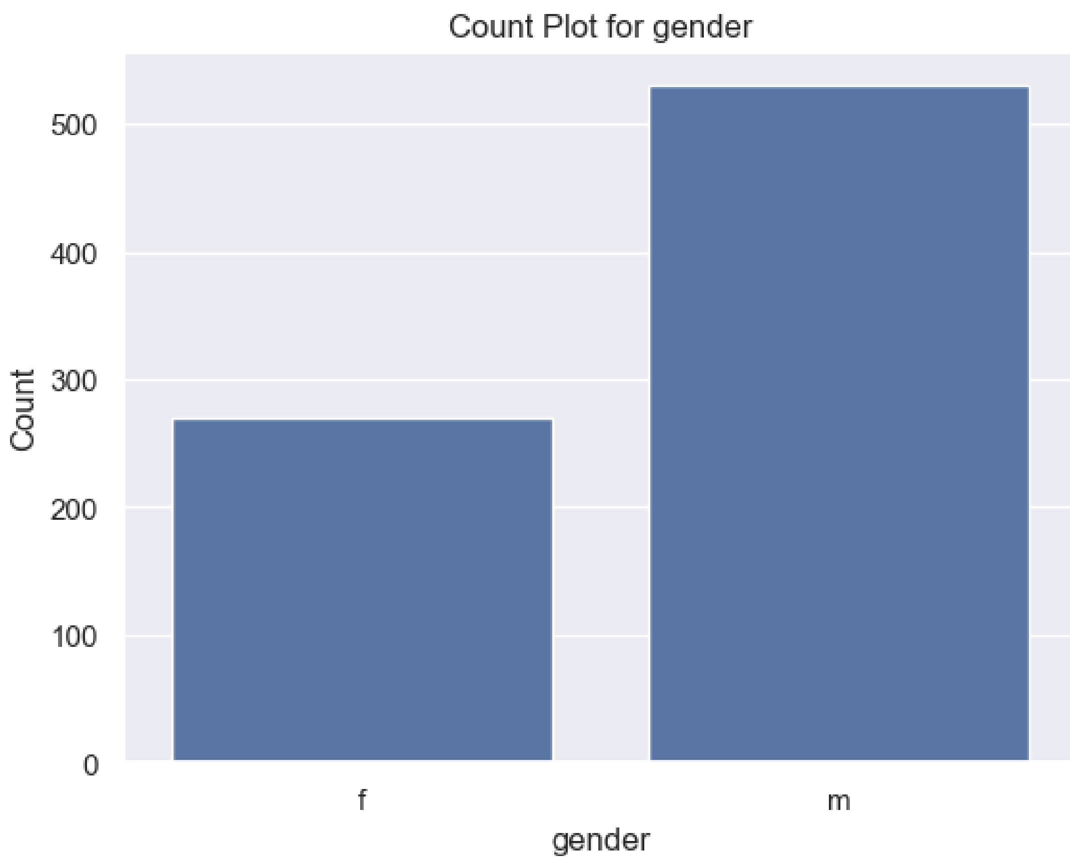

Count Plot for A7_Score
500
400
300
200
100
0
Count
0
1
A7_Score

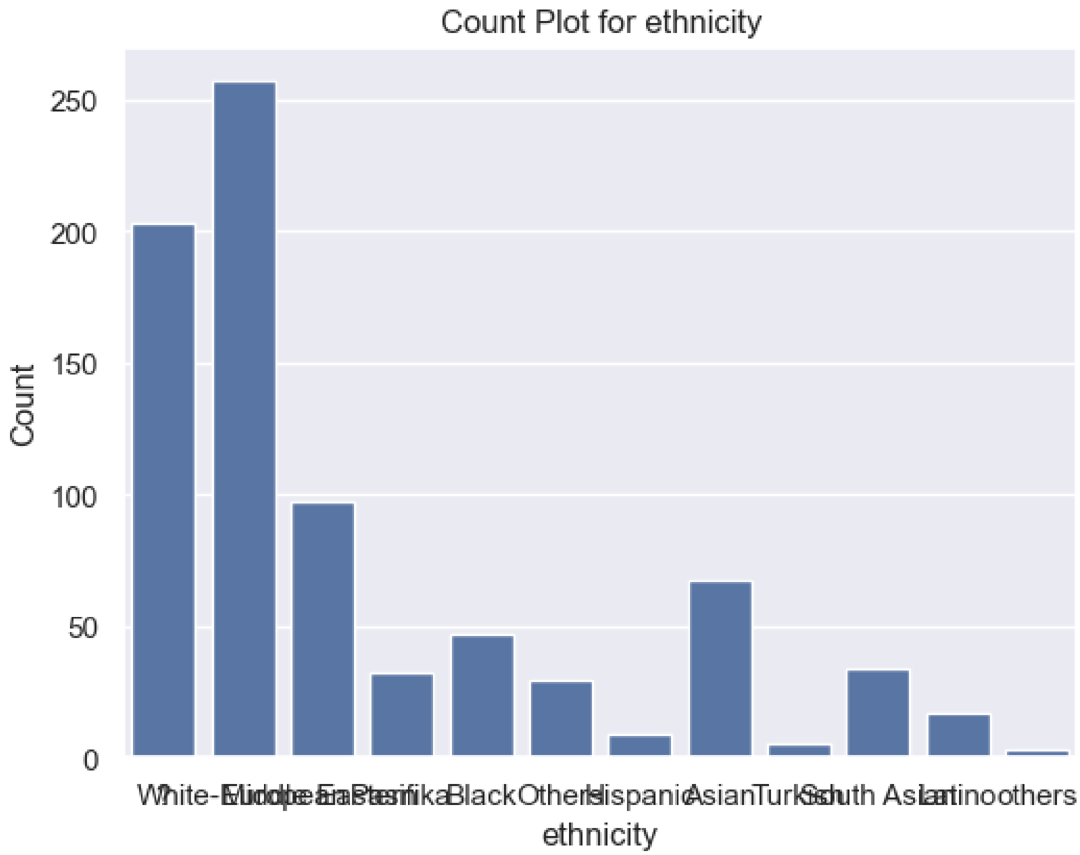


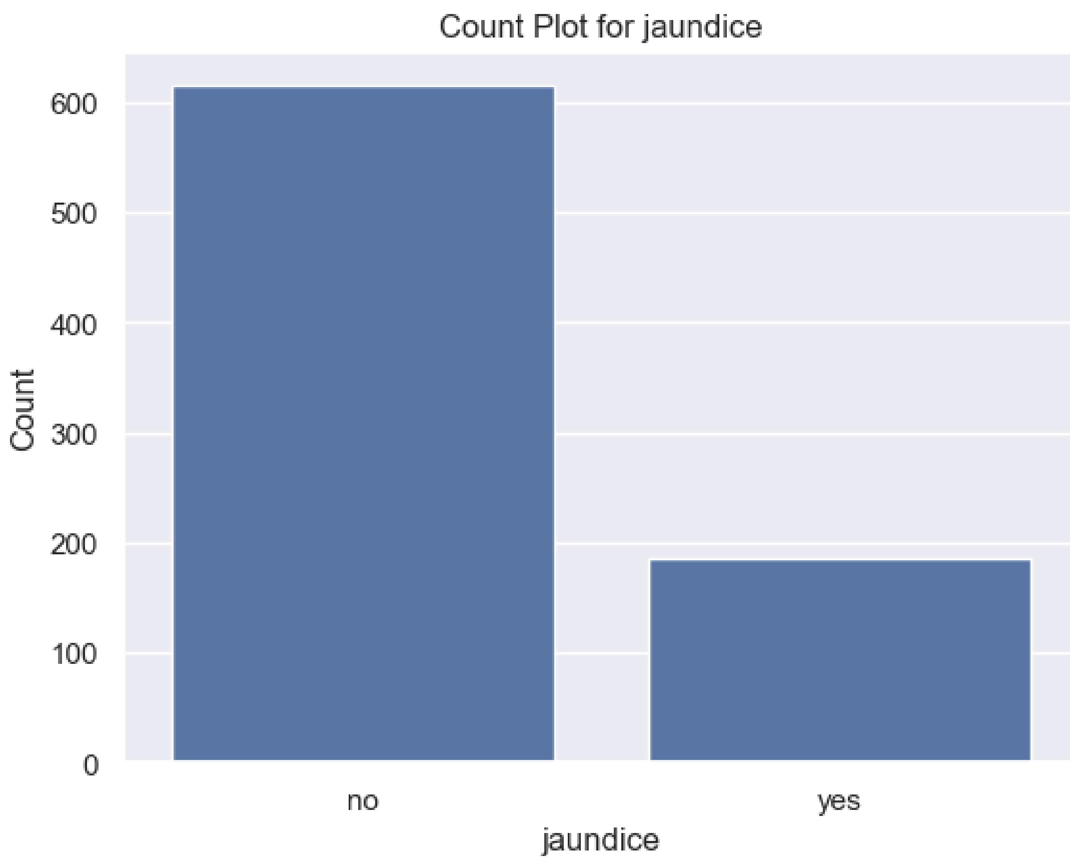
Count Plot for A8_Score
Count
400
350
300
250
200
150
100
50
0
0
1
A8_Score

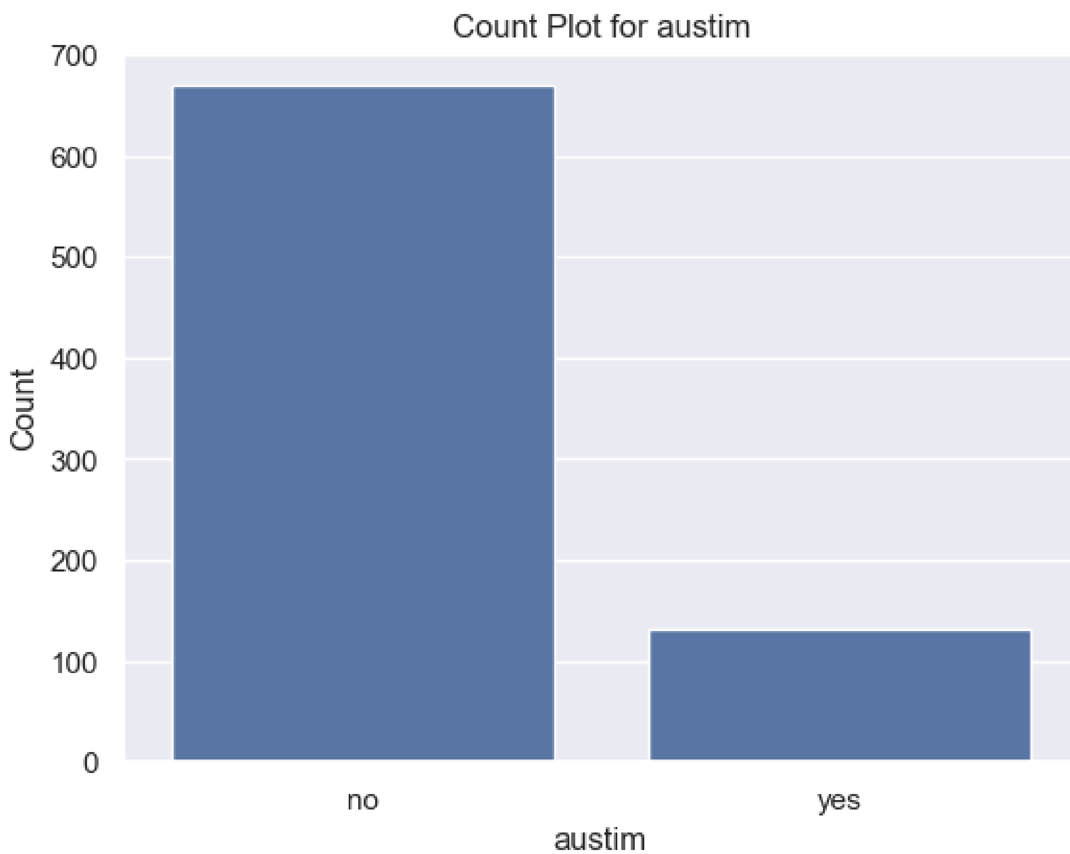

Count Plot for A9_Score
400
350
300
250
200
150
100
50
0
Count
0
1
A9_Score

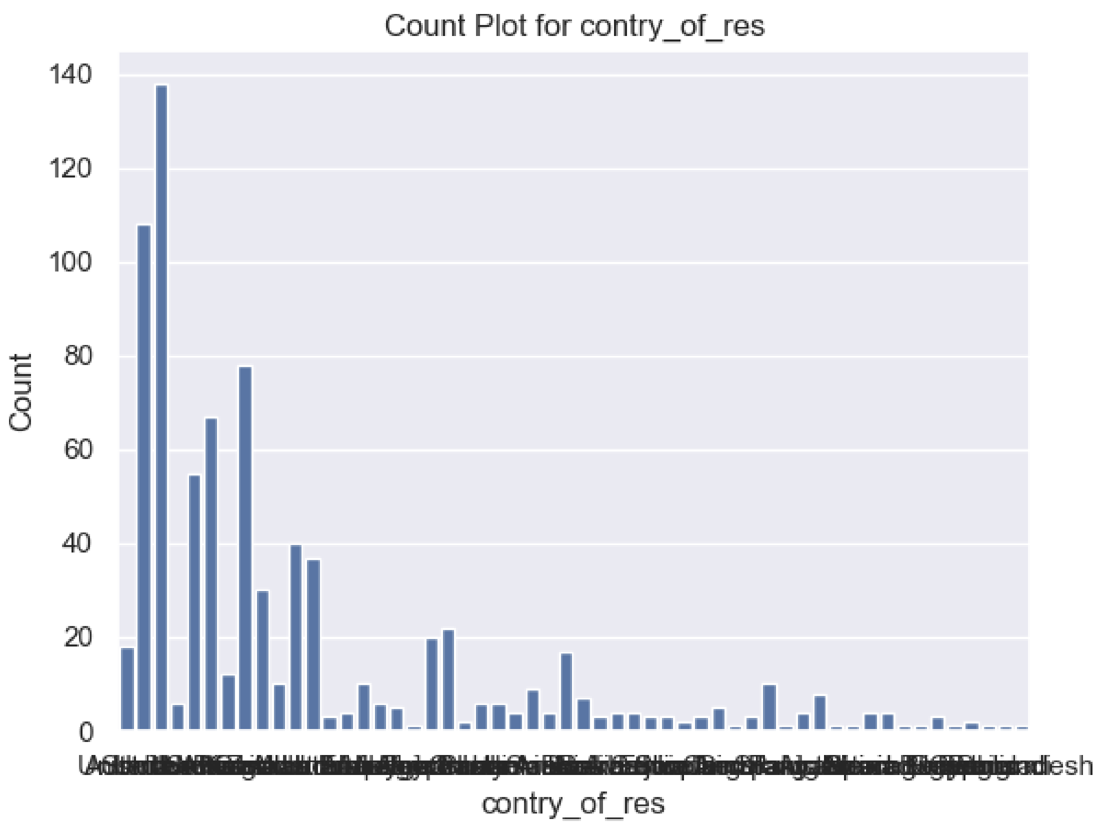

Count Plot for A10_Score
500
400
300
200
100
0
Count
0
1
A10_Score

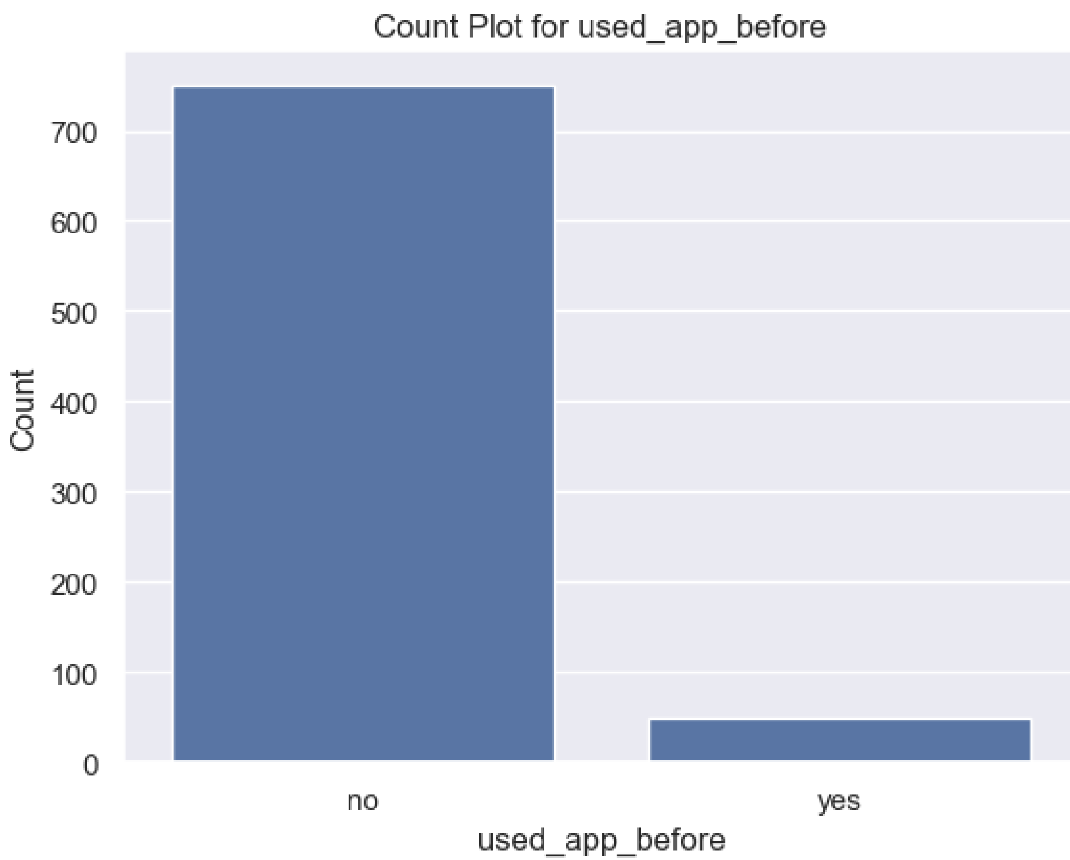

Count Plot for gender
Count
0
100
200
300
400
500
f
m
gender

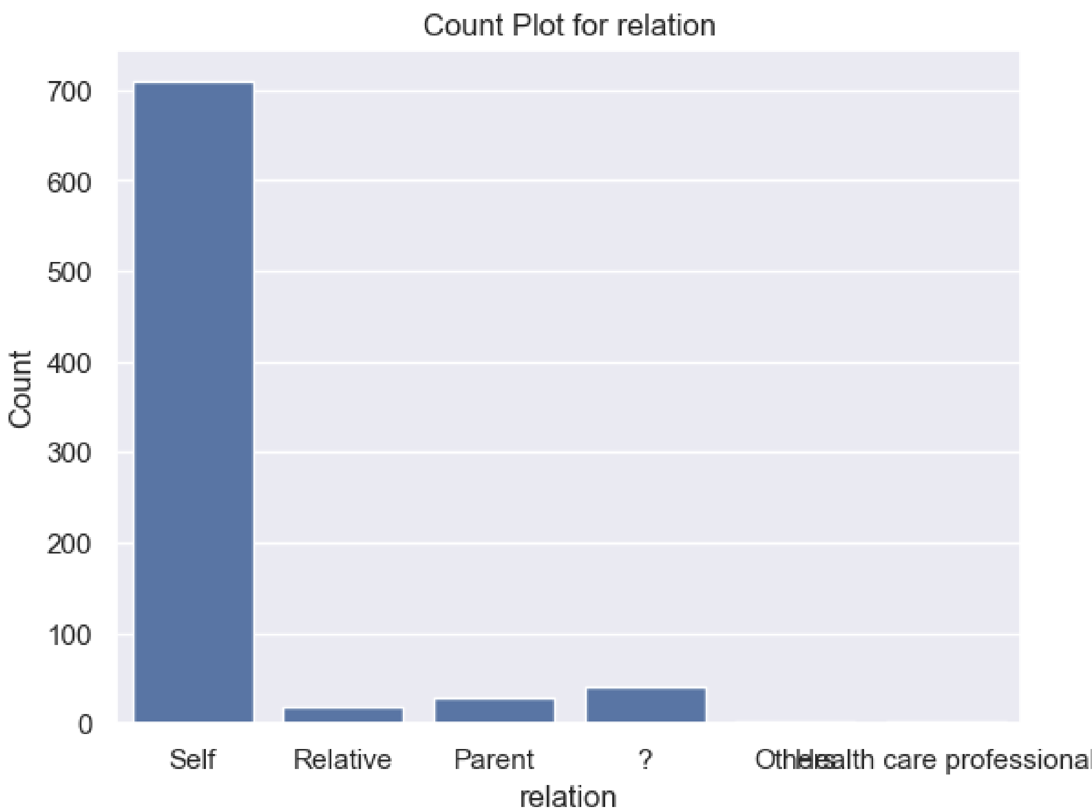

Count Plot for ethnicity
Count
250
200
150
100
50
0
Black
Asian
others
ethnicity


Count Plot for jaundice
600
500
400
300
200
100
0
Count
no
yes
jaundice


Count Plot for austim
700
600
500
400
300
200
100
0
Count
no
yes
austim


Count Plot for contry_of_res
Count
0
20
40
60
80
100
120
140
contry_of_res


Count Plot for used_app_before
700
600
500
400
300
200
100
0
Count
no
yes
used_app_before



[42]:
```
df["Class/ASD"].value_counts()
```

[42]:
```
Class/ASD
0    639
1    161
Name: count, dtype: int64
```

Handling missing values in Categorical Columns

[43]:
```
df["ethnicity"] = df["ethnicity"].replace({"?": "Others", "others": "Others"})
```

[44]:
```
df["ethnicity"].unique()
```

[44]:
```
array(['Others', 'White-European', 'Middle Eastern ', 'Pasifika', 'Black',
       'Hispanic', 'Asian', 'Turkish', 'South Asian', 'Latino'],
      dtype=object)
```

[45]:
```
df["relation"].unique()
```

[45]:
```
array(['Self', 'Relative', 'Parent', '?', 'Others',
       'Health care professional'], dtype=object)
```

[46]:
```
df["relation"] = df["relation"].replace(
    {"?": "Others",
     "Relative": "Others",
     "Parent": "Others",
     "Health care professional": "Others"}
)
```

[47]:
```
df["relation"].unique()
```

[47]:
```
array(['Self', 'Others'], dtype=object)
```

[48]:
```
df.head()
```

[48]:
```
   A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  A6_Score  A7_Score  \
0         1         0         1         0         1         0         1
1         0         0         0         0         0         0         0
2         1         1         1         1         1         1         1
3         0         0         0         0         0         0         0
4         0         0         0         0         0         0         0

   A8_Score  A9_Score  A10_Score  age gender       ethnicity jaundice austim  \
0         0         1          1   38      f          Others       no     no
1         0         0          0   47      m          Others       no     no
2         1         1          1    7      m  White-European       no    yes
3         0         0          0   23      f          Others       no     no
4         0         0          0   43      m          Others       no     no

   contry_of_res used_app_before     result relation  Class/ASD
0        Austria              no   6.351166     Self          0
1          India              no   2.255185     Self          0
2  United States              no  14.851484     Self          1
3  United States              no   2.276617     Self          0
4   South Africa              no  -4.777286     Self          0
```

Label Encoding

[50]:
```
# identify columns with "object" data type
object_columns = df.select_dtypes(include=["object"]).columns
print(object_columns)
```

```
Index(['gender', 'ethnicity', 'jaundice', 'austim', 'contry_of_res',
       'used_app_before', 'relation'],
      dtype='object')
```

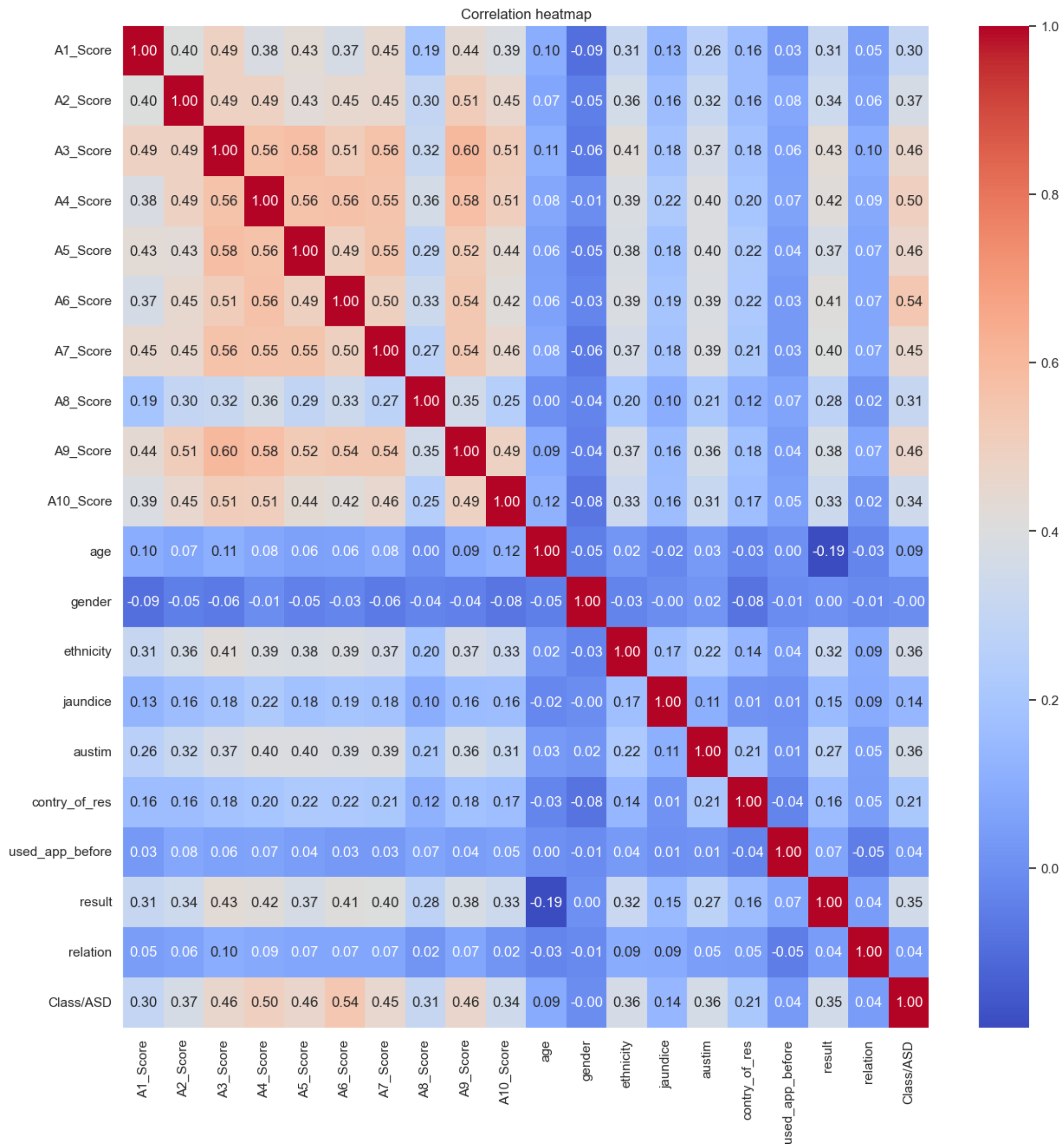
[52]:
```
# initialize a dictionary to store the encoders
encoders = {}

# apply label encoding and store the encoders
```

```
for column in object_columns:
  label_encoder = LabelEncoder()
  df[column] = label_encoder.fit_transform(df[column])
  encoders[column] = label_encoder   # saving the encoder for this column


# save the encoders as a pickle file
with open("encoders.pkl", "wb") as f:
  pickle.dump(encoders, f)

encoders
```

[52]:
```
{'gender': LabelEncoder(),
 'ethnicity': LabelEncoder(),
 'jaundice': LabelEncoder(),
 'austim': LabelEncoder(),
 'contry_of_res': LabelEncoder(),
 'used_app_before': LabelEncoder(),
 'relation': LabelEncoder()}
```

Heat Map Visualization

[53]:
```
# correlation matrix
plt.figure(figsize=(15, 15))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation heatmap")
plt.show()
```



Observation - Moderate Positive Correlations: Notable positive relationships exist between some scores, such as A1_Score and A2_Score.

- Negative Correlations: Age negatively correlates with both result and Class/ASD.

Key Correlations:

- "Result" is strongly positively correlated with "Class/ASD".
- "Used_app_before" and "Relation" show moderate positive correlations with "Result" and "Class/ASD".

Model Building

[56]:
```python
X = df.drop(columns=["Class/ASD"])
y = df["Class/ASD"]
```

[58]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
```

Synthetic Minority Oversampling Technique(SMOTE)

[59]:
```python
smote = SMOTE(random_state=32)
```

[60]:
```python
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)
```

[61]:
```python
print(y_train_smote.shape)
```

```
(906,)
```

[62]:
```python
print(y_train_smote.value_counts())
```

```
Class/ASD
0    453
1    453
Name: count, dtype: int64
```

Synthetic Minority Oversampling Technique (SMOTE) to balance an imbalanced dataset. It initializes SMOTE, applies it to the training data, and then prints the shape and class distribution of the resampled data, showing that the classes are now balanced. This is crucial for training a machine learning model effectively without bias.

Model Training

[64]:
```python
# dictionary of classifiers
models = {
    "Decision Tree": DecisionTreeClassifier(random_state=42),
    "Random Forest": RandomForestClassifier(random_state=42),
    "XGBoost": XGBClassifier(random_state=42)
}
```

[65]:
```python
# dictionary to store the cross validation results
cv_scores = {}

# perform 5-fold cross validation for each model
for model_name, model in models.items():
  print(f"Training {model_name} with default parameters...")
  scores = cross_val_score(model, X_train_smote, y_train_smote, cv=5,␣
↪scoring="accuracy")
  cv_scores[model_name] = scores
  print(f"{model_name} Cross-Validation Accuracy: {np.mean(scores):.2f}")
  print("-"*50)
```

```
Training Decision Tree with default parameters…
Decision Tree Cross-Validation Accuracy: 0.86
--------------------------------------------------
Training Random Forest with default parameters…
Random Forest Cross-Validation Accuracy: 0.91
--------------------------------------------------
Training XGBoost with default parameters…
XGBoost Cross-Validation Accuracy: 0.90
--------------------------------------------------
```

Observation

We performed 5-fold cross-validation on three different machine learning models: Decision Tree, Random Forest, and XGBoost. The purpose of cross-validation is to evaluate the performance of these models by splitting the training data into five subsets, training the model on four of these subsets, and then testing it on the remaining subset. This process is repeated five times, with each subset used once as the test set.

Here are the details of the results:

Decision Tree Model:

Cross-Validation Accuracy: 0.86

This means that the Decision Tree model achieved an average accuracy of 86% across the 5 folds.

Random Forest Model:

Cross-Validation Accuracy: 0.91

The Random Forest model performed better, with an average accuracy of 91% across the 5 folds.

XGBoost Model:

Cross-Validation Accuracy: 0.90

The XGBoost model also performed well, with an average accuracy of 90% across the 5 folds.

[ ]:

```

```