EDA

March 28, 2025

1 Early Autism Detection

1.1 Exploratory Data Analysis

1.1.1 Load The Autistic Spectrum Disorder Screening Data for Children Dataset

Description: This dataset contains information related to the screening of autistic spectrum disorder (ASD) in children. It includes various demographic and behavioral features that are used to identify potential ASD cases.

Attributes:

- **A1_Score:** Integer - The answer code for the first question in the AQ-10-Child questionnaire (0 or 1).
- **A2_Score:** Integer - The answer code for the second question in the AQ-10-Child questionnaire (0 or 1).
- **A3_Score:** Integer - The answer code for the third question in the AQ-10-Child questionnaire (0 or 1).
- **A4_Score:** Integer - The answer code for the fourth question in the AQ-10-Child questionnaire (0 or 1).
- **A5_Score:** Integer - The answer code for the fifth question in the AQ-10-Child questionnaire (0 or 1).
- **A6_Score:** Integer - The answer code for the sixth question in the AQ-10-Child questionnaire (0 or 1).
- **A7_Score:** Integer - The answer code for the seventh question in the AQ-10-Child questionnaire (0 or 1).
- **A8_Score:** Integer - The answer code for the eighth question in the AQ-10-Child questionnaire (0 or 1).
- **A9_Score:** Integer - The answer code for the ninth question in the AQ-10-Child questionnaire (0 or 1).
- **A10_Score:** Integer - The answer code for the tenth question in the AQ-10-Child questionnaire (0 or 1).
- **age:** Integer - Age of the individual in years.
- **gender:** Categorical - Gender of the individual (Male or Female).

- **ethnicity:** Categorical - List of common ethnicities in text format.
- **jaundice:** Binary - Whether the individual was born with jaundice (yes or no).
- **autism:** Binary - Whether any immediate family member has a pervasive developmental disorder (PDD) (yes or no).
- **country_of_res:** Categorical - List of countries in text format.
- **used_app_before:** Binary - Whether the user has used a screening app before (yes or no).
- **result:** Integer - The final score obtained based on the scoring algorithm of the screening method used.
- **age_desc:** Categorical - Description of the age category.
- **relation:** Categorical - The person completing the test (Parent, self, caregiver, medical staff, clinician, etc.).
- **class:** Binary - The target variable indicating whether the individual is classified as having ASD (yes or no).

Source: Thabtah, F. (2017). Autistic Spectrum Disorder Screening Data for Children [Dataset]. UCI Machine Learning Repository. Retrieved from https://doi.org/10.24432/C5659W.

[1]:
```
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.impute import SimpleImputer
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from ucimlrepo import fetch_ucirepo
from wordcloud import WordCloud
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import squarify
```

[2]:
```
autistic_spectrum_disorder_screening_data_for_children = fetch_ucirepo( id=419 )
X = autistic_spectrum_disorder_screening_data_for_children.data.features
y = autistic_spectrum_disorder_screening_data_for_children.data.targets
df_original = pd.concat( [X, y], axis=1 )
df = df_original.copy()
```

1.2 Dataset Inspection

The dataset has **292** records and **21** features (variables).

[3]:
```
feature_names = df.columns
print( feature_names )
print( df.shape )
```

```
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', 'autism', 'country_of_res', 'used_app_before',
       'result', 'age_desc', 'relation', 'class'],
      dtype='object')
(292, 21)
```

1.2.1 Data Types and Data Head and Tail

[4]:
```
print( df.dtypes )
```

```
A1_Score             int64
A2_Score             int64
A3_Score             int64
A4_Score             int64
A5_Score             int64
A6_Score             int64
A7_Score             int64
A8_Score             int64
A9_Score             int64
A10_Score            int64
age                float64
gender              object
ethnicity           object
jaundice            object
autism              object
country_of_res      object
used_app_before     object
result               int64
age_desc            object
relation            object
class               object
dtype: object
```

[5]:
```
df.head()
```

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

   A8_Score  A9_Score  A10_Score  …  gender          ethnicity jaundice  \
0         1         0          0  …       m             Others       no
1         1         0          0  …       m  'Middle Eastern '       no
2         1         0          0  …       m                NaN       no
3         0         0          1  …       f                NaN      yes
4         1         1          1  …       m             Others      yes
```

```
  autism   country_of_res used_app_before result      age_desc relation class
0     no           Jordan              no      5  '4-11 years'   Parent    NO
1     no           Jordan              no      5  '4-11 years'   Parent    NO
2     no           Jordan             yes      5  '4-11 years'      NaN    NO
3     no           Jordan              no      4  '4-11 years'      NaN    NO
4     no  'United States'              no     10  '4-11 years'   Parent   YES

[5 rows x 21 columns]
```

[6]:
```
df.tail()
```

[6]:
```
     A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  A6_Score  A7_Score  \
287         1         1         1         1         1         1         1
288         1         0         0         0         1         0         1
289         1         0         1         1         1         1         1
290         1         1         1         0         1         1         1
291         0         0         1         0         1         0         1

     A8_Score  A9_Score  A10_Score  …  gender        ethnicity jaundice  \
287         1         1          1  …       f  White-European      yes
288         0         0          1  …       f  White-European      yes
289         0         0          1  …       m          Latino       no
290         1         1          1  …       m    'South Asian'      no
291         0         0          0  …       f    'South Asian'      no

    autism    country_of_res used_app_before result      age_desc relation  \
287    yes  'United Kingdom'              no     10  '4-11 years'   Parent
288    yes         Australia              no      4  '4-11 years'   Parent
289     no            Brazil              no      7  '4-11 years'   Parent
290     no             India              no      9  '4-11 years'   Parent
291     no             India              no      3  '4-11 years'   Parent

    class
287   YES
288    NO
289   YES
290   YES
291    NO

[5 rows x 21 columns]
```

1.2.2 Missing Values

The columns with missing values are **ethnicity** with **43** missing values, **relation** with **43** missing values, and **age** with **4** missing values.

[7]:
```
df.isna().sum()
```

[7]:
```
A1_Score           0
A2_Score           0
A3_Score           0
A4_Score           0
A5_Score           0
A6_Score           0
A7_Score           0
A8_Score           0
A9_Score           0
A10_Score          0
age                4
gender             0
ethnicity         43
jaundice           0
autism             0
country_of_res     0
used_app_before    0
result             0
age_desc           0
relation          43
class              0
dtype: int64
```

1.2.3 Duplicates

There are 2 duplicates but they have different values in different columns so I'll keep them.

[8]:
```
duplicates = df.duplicated()
print( df[duplicates] )
```

```
    A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  A6_Score  A7_Score  \
84         0         0         1         0         1         1         1
93         0         0         1         1         1         1         1

    A8_Score  A9_Score  A10_Score  …  gender ethnicity jaundice autism  \
84         0         1          1  …       m     Asian       no     no
93         1         1          1  …       m     Asian       no     no

   country_of_res used_app_before result      age_desc relation class
84          India              no      6  '4-11 years'   Parent    NO
93          India              no      8  '4-11 years'   Parent   YES

[2 rows x 21 columns]
```

1.2.4 Outliers

There's **1 outlier** in the **result** column and this is because the **result** column is obtained by adding the **first ten** columns. The value for these first ten columns is 0 and therefore the value for the **result** column is 0. I'll ignore this outlier since it is a valid record.

[9]:

```
def detect_outliers_iqr( df, column ):
    Q1 = df[column].quantile( 0.25 )
    Q3 = df[column].quantile( 0.75 )
    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    outliers = df[( df[column] < lower_bound ) | ( df[column] > upper_bound )]

    return outliers

numerical_features = df.select_dtypes( include=['number'] ).columns

for feature in numerical_features:
    outliers = detect_outliers_iqr( df, feature )
    print( f"Number of outliers in {feature}: {len( outliers )}" )
    if not outliers.empty:
        print( outliers )
```

```
Number of outliers in A1_Score: 0
Number of outliers in A2_Score: 0
Number of outliers in A3_Score: 0
Number of outliers in A4_Score: 0
Number of outliers in A5_Score: 0
Number of outliers in A6_Score: 0
Number of outliers in A7_Score: 0
Number of outliers in A8_Score: 0
Number of outliers in A9_Score: 0
Number of outliers in A10_Score: 0
Number of outliers in age: 0
Number of outliers in result: 1
     A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  A6_Score  A7_Score  \
137         0         0         0         0         0         0         0

     A8_Score  A9_Score  A10_Score  …  gender ethnicity jaundice autism  \
137         0         0          0  …       f  Hispanic       no     no

      country_of_res used_app_before result      age_desc relation class
137  'United States'              no      0  '4-11 years'   Parent    NO

[1 rows x 21 columns]
```

[10]:

```
for feature in numerical_features:
    outliers = detect_outliers_iqr( df, feature )
    print( f"Number of outliers in {feature}: {len( outliers )}" )
    if not outliers.empty:
        print( f"Outliers in {feature}:" )
```

```
        print( outliers[['result']] )
```

```
Number of outliers in A1_Score: 0
Number of outliers in A2_Score: 0
Number of outliers in A3_Score: 0
Number of outliers in A4_Score: 0
Number of outliers in A5_Score: 0
Number of outliers in A6_Score: 0
Number of outliers in A7_Score: 0
Number of outliers in A8_Score: 0
Number of outliers in A9_Score: 0
Number of outliers in A10_Score: 0
Number of outliers in age: 0
Number of outliers in result: 1
Outliers in result:
     result
137       0
```

1.2.5 Data Imbalance

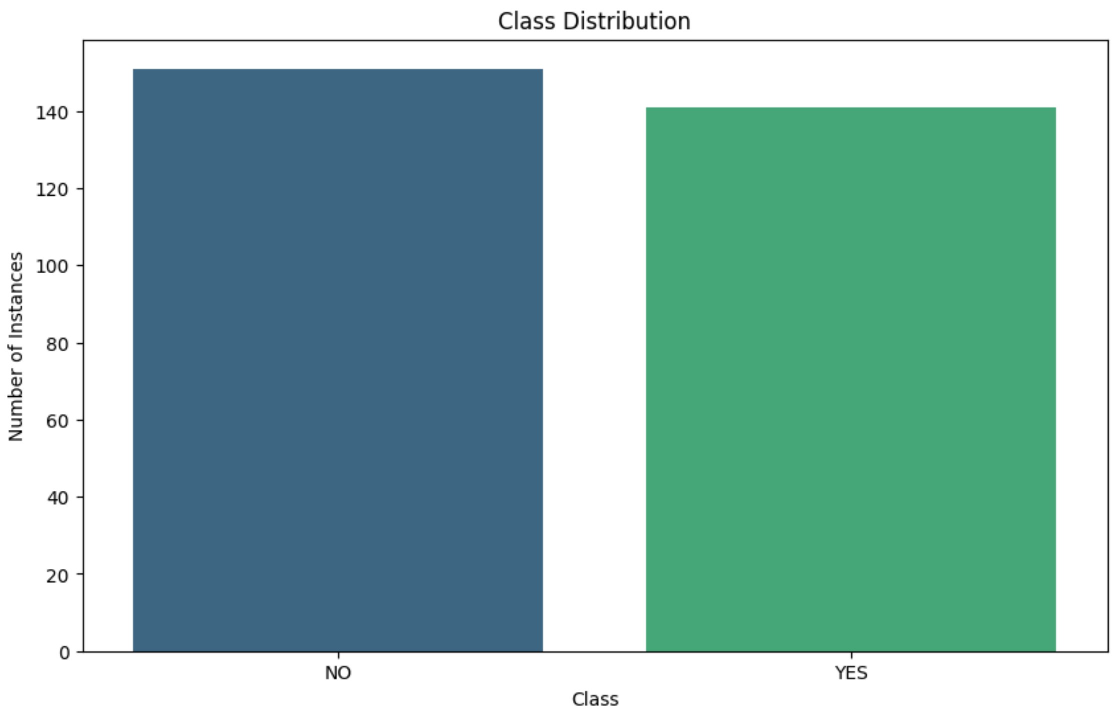
The dataset is relatively balanced with a slight majority of **NO** instances. No concern for data imbalance.

[11]:
```
class_distribution = df['class'].value_counts()

print( "Class distribution:" )
print( class_distribution )

class_percentage = df['class'].value_counts( normalize = True ) * 100

print( "\nClass percentage distribution:" )
for index, value in class_percentage.items():
    print( f"{index}: {value:.2f}%" )
```

```
Class distribution:
class
NO     151
YES    141
Name: count, dtype: int64

Class percentage distribution:
NO: 51.71%
YES: 48.29%
```

[12]:
```
class_distribution_df = class_distribution.reset_index()
class_distribution_df.columns = ['class', 'count']

plt.figure( figsize = ( 10, 6 ) )
```

```
sns.barplot( data = class_distribution_df, x = 'class', y = 'count', palette =␣
↪'viridis', hue = 'class', dodge = False )
plt.title( 'Class Distribution' )
plt.xlabel( 'Class' )
plt.ylabel( 'Number of Instances' )
plt.legend( [],[], frameon = False )
plt.show()
```



1.3 Data Cleaning

1.3.1 Imputing missing values for "ethnicity" and "relation" with "Unknown"

[13]:
```
df.fillna( {"ethnicity": "Unknown"}, inplace = True )
df.fillna( {"relation": "Unknown"}, inplace = True )
```

1.3.2 Deleting result and age_desc column

[14]:
```
df = df.drop( columns = ["result", "age_desc"] )
```

1.3.3 Imputing missing values for age by median

[15]:
```
simple_imputer = SimpleImputer( strategy = 'median' )
df['age'] = simple_imputer.fit_transform( df[['age']] )
```

1.3.4 Converting categorical columns to category data type

[16]:
```
categorical_columns = ['gender', 'ethnicity', 'jaundice', 'autism',␣
↪'country_of_res', 'used_app_before', 'relation', 'class']
for col in categorical_columns:
    df[col] = df[col].astype( 'category' )
```

1.4 Data Preprocessing

1.4.1 Unique Values for Categorical columns

[17]:
```
categorical_columns = df.select_dtypes( include = ['object', 'category'] ).
↪columns

for col in categorical_columns:
    unique_values = df[col].unique()
    print( f"Unique values in '{col}': {unique_values}" )
```

```
Unique values in 'gender': ['m', 'f']
Categories (2, object): ['f', 'm']
Unique values in 'ethnicity': ['Others', ''Middle Eastern '', 'Unknown', 'White-
European', 'Black', …, 'Asian', 'Pasifika', 'Hispanic', 'Turkish', 'Latino']
Length: 11
Categories (11, object): [''Middle Eastern '', ''South Asian'', 'Asian',
'Black', …, 'Pasifika', 'Turkish', 'Unknown', 'White-European']
Unique values in 'jaundice': ['no', 'yes']
Categories (2, object): ['no', 'yes']
Unique values in 'autism': ['no', 'yes']
Categories (2, object): ['no', 'yes']
Unique values in 'country_of_res': ['Jordan', ''United States'', 'Egypt',
''United Kingdom'', 'Bahrain', …, 'Mexico', ''Isle of Man'', 'Libya', 'Ghana',
'Bhutan']
Length: 52
Categories (52, object): [''Costa Rica'', ''Isle of Man'', ''New Zealand'',
''Saudi Arabia'', …, 'Russia', 'Sweden', 'Syria', 'Turkey']
Unique values in 'used_app_before': ['no', 'yes']
Categories (2, object): ['no', 'yes']
Unique values in 'relation': ['Parent', 'Unknown', 'Self', 'Relative', ''Health
care professional'', 'self']
Categories (6, object): [''Health care professional'', 'Parent', 'Relative',
'Self', 'Unknown', 'self']
Unique values in 'class': ['NO', 'YES']
Categories (2, object): ['NO', 'YES']
```

1.4.2 Clean the ethnicity, country_of_res column, and relation

[18]:
```
def clean_columns( df, columns ):

    for col in columns:
        df[col] = df[col].str.strip()
        df[col] = df[col].str.replace(r'[^a-zA-Z\s-]', '', regex=True)
    return df

columns_to_clean = ['ethnicity', 'country_of_res', 'relation']
df = clean_columns( df, columns_to_clean )

df['relation'] = df['relation'].replace( {'self': 'Self', 'Self': 'Self'} )
```

1.4.3 Label Encoding and One-hot encoding Categorical Columns

[19]:
```
label_encode_columns = ["gender", "jaundice", "autism", "used_app_before",␣
↪"class"]
label_encoders = {}
for col in label_encode_columns:
    le = LabelEncoder()
    df[col] = le.fit_transform( df[col] )
    label_encoders[col] = le

one_hot_encoded_columns = ["ethnicity", "country_of_res", "relation"]
df = pd.get_dummies( df, columns = one_hot_encoded_columns )
```

1.4.4 Saving dataframe to CSV for future analysis

[20]:
```
df.to_csv( 'earlyAutism.csv', index = False )
```

1.4.5 MinMax Scaling Will Be Applied Before Training ML Models

[21]:
```
numerical_columns = df.select_dtypes( include = ['number'] ).columns
scaler = MinMaxScaler()
df[numerical_columns] = scaler.fit_transform( df[numerical_columns] )
```

1.5 Data Analysis And Visualization

1.5.1 Summary Statistics

[22]:
```
print( df.describe() )
```

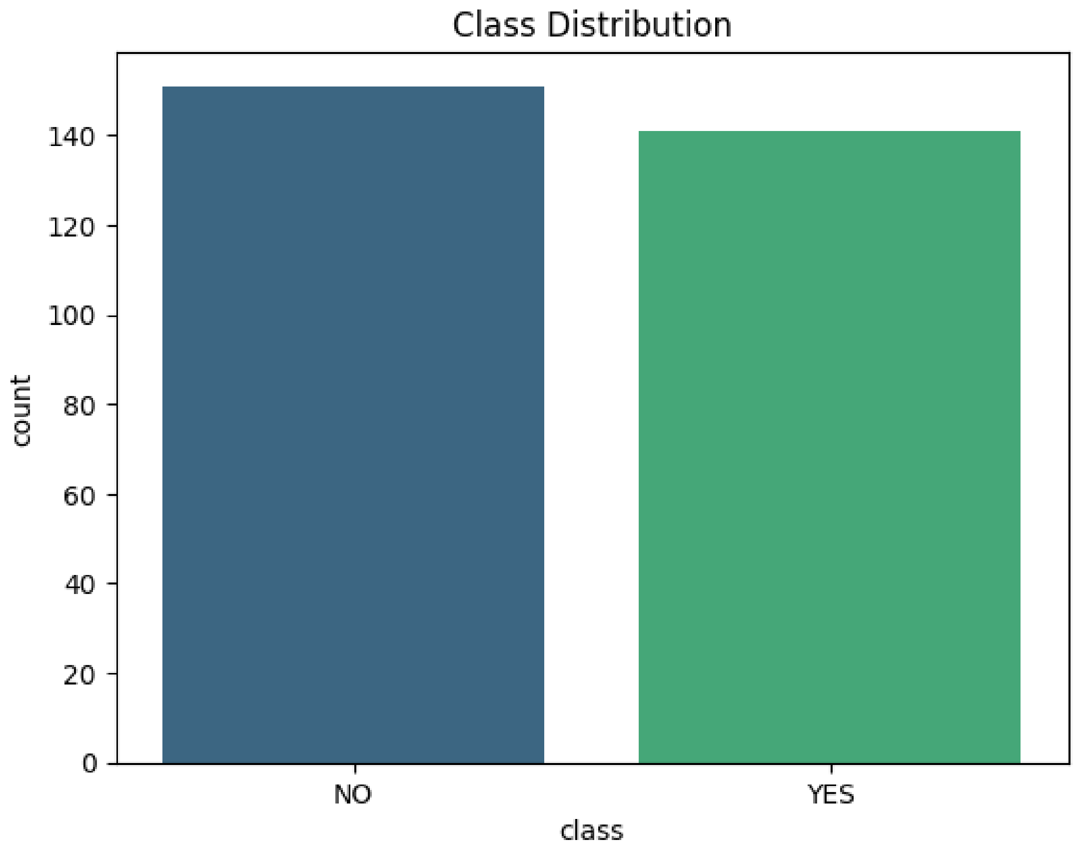
```
         A1_Score    A2_Score    A3_Score    A4_Score    A5_Score    A6_Score  \
count  292.000000  292.000000  292.000000  292.000000  292.000000  292.000000
mean     0.633562    0.534247    0.743151    0.551370    0.743151    0.712329
std      0.482658    0.499682    0.437646    0.498208    0.437646    0.453454
min      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
```

```
25%       0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
50%       1.000000    1.000000    1.000000    1.000000    1.000000    1.000000
75%       1.000000    1.000000    1.000000    1.000000    1.000000    1.000000
max       1.000000    1.000000    1.000000    1.000000    1.000000    1.000000

          A7_Score    A8_Score    A9_Score   A10_Score         age      gender  \
count   292.000000  292.000000  292.000000  292.000000  292.000000  292.000000
mean      0.606164    0.496575    0.493151    0.726027    0.335616    0.712329
std       0.489438    0.500847    0.500811    0.446761    0.335643    0.453454
min       0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
25%       0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
50%       1.000000    0.000000    0.000000    1.000000    0.285714    1.000000
75%       1.000000    1.000000    1.000000    1.000000    0.571429    1.000000
max       1.000000    1.000000    1.000000    1.000000    1.000000    1.000000

          jaundice      autism  used_app_before       class
count   292.000000  292.000000       292.000000  292.000000
mean      0.273973    0.167808         0.037671    0.482877
std       0.446761    0.374337         0.190727    0.500565
min       0.000000    0.000000         0.000000    0.000000
25%       0.000000    0.000000         0.000000    0.000000
50%       0.000000    0.000000         0.000000    0.000000
75%       1.000000    0.000000         0.000000    1.000000
max       1.000000    1.000000         1.000000    1.000000
```

1.5.2 Distribution of the target variable

The **NO** class has a bit higher count than the **YES** class but ultimately the two are relatively balanced.

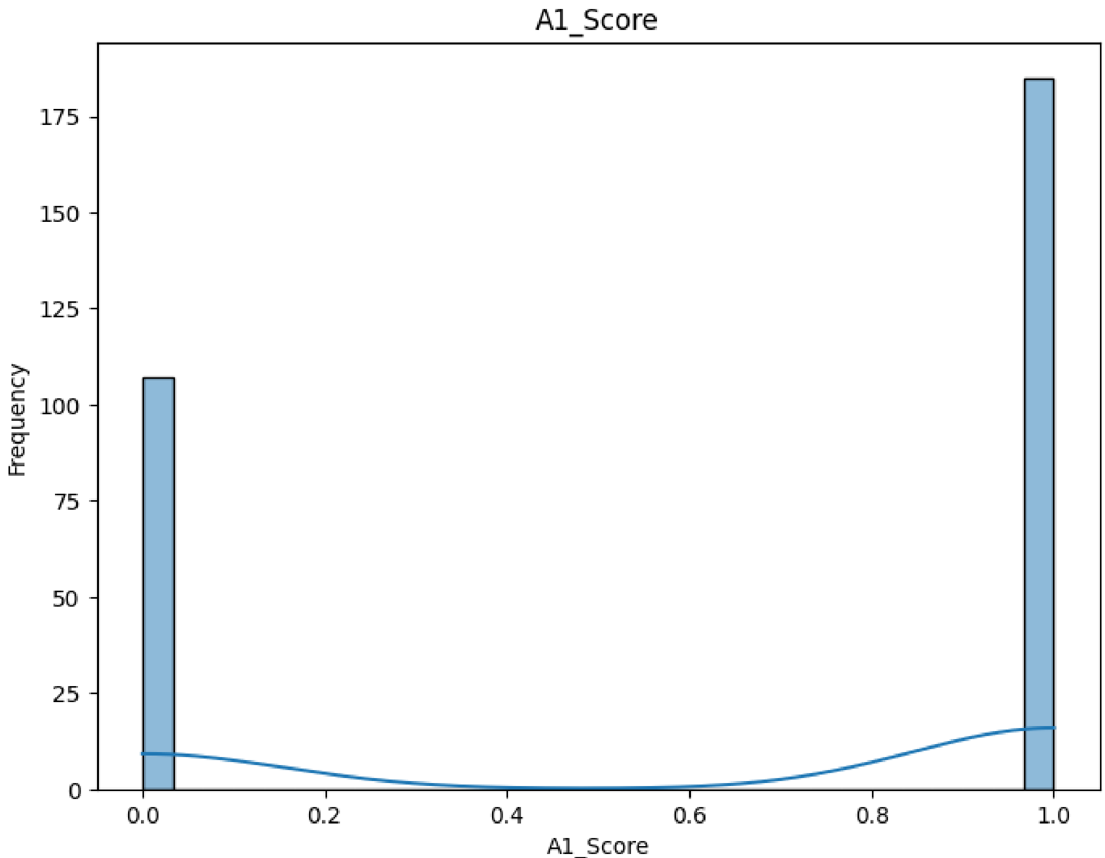
[23]:
```
sns.countplot( x = 'class', data = df_original, hue = 'class', palette =␣
 ↪'viridis' )
plt.title( 'Class Distribution' )
plt.show()
```



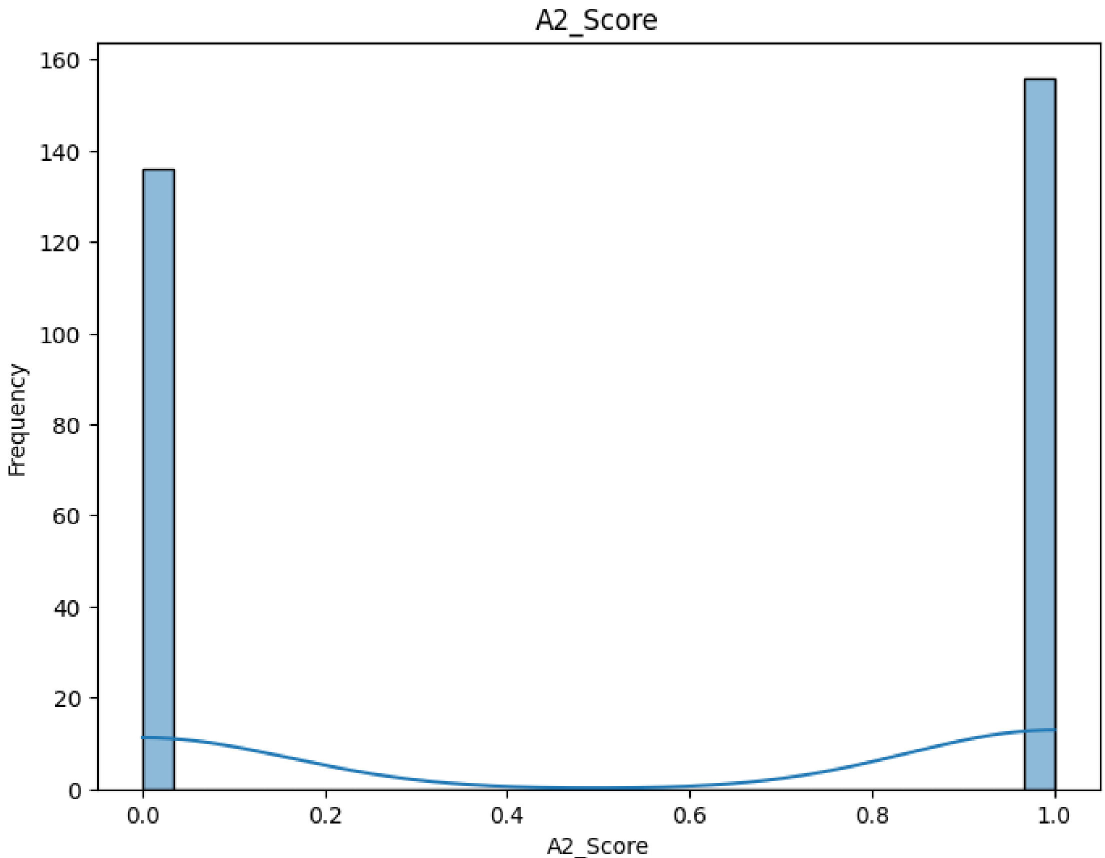
1.5.3 Distibution for Numerical Features

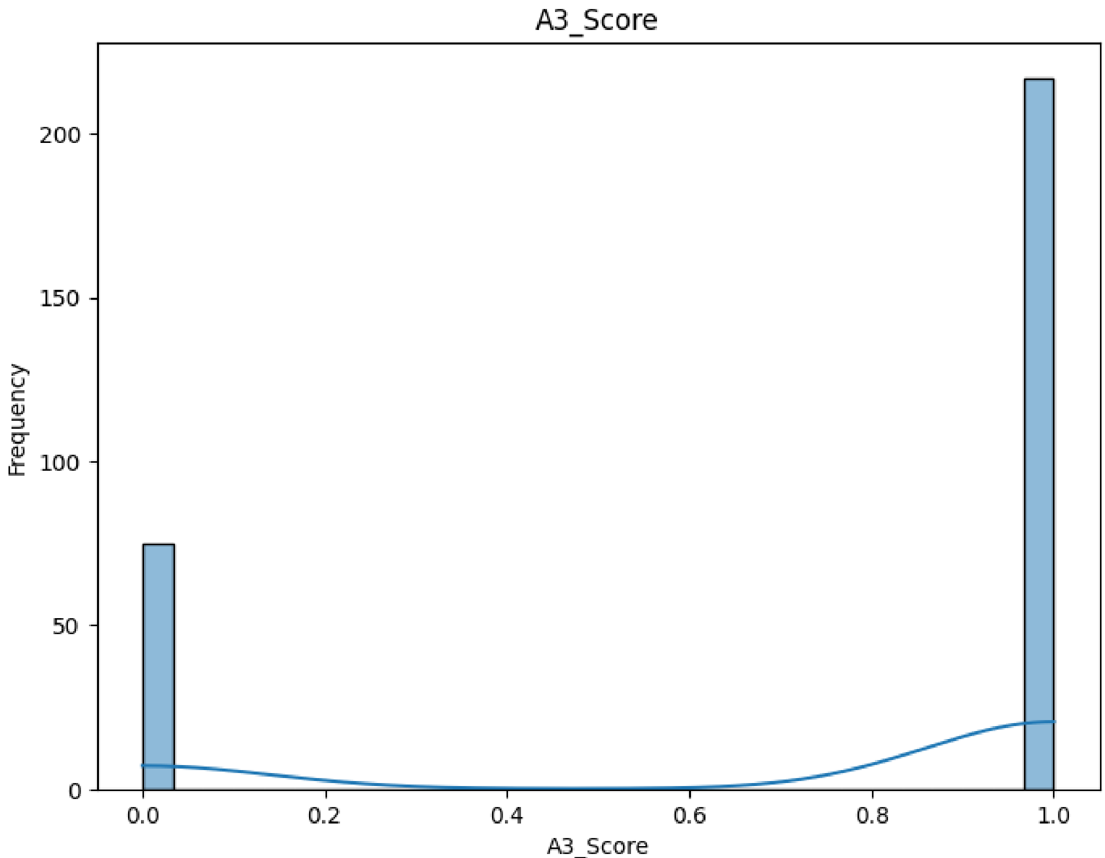
age has right skewed distribution whereas **result** has left skewed distribution.

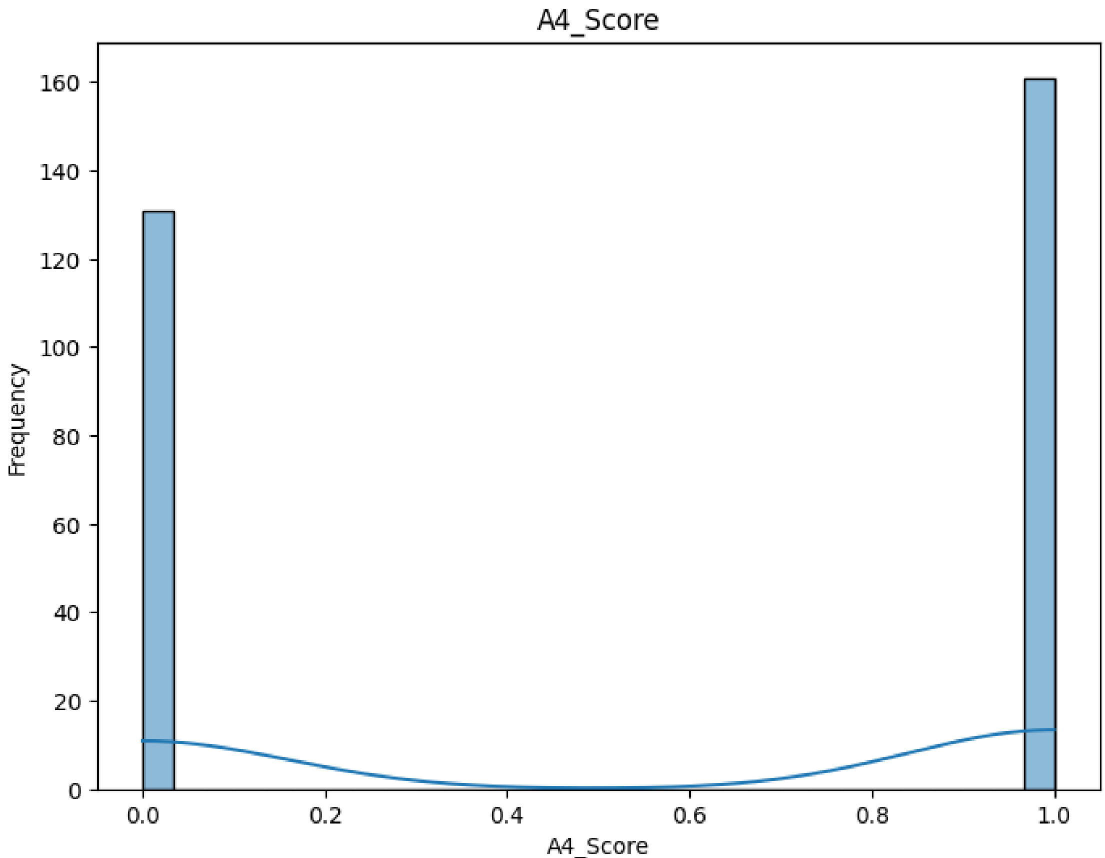
[24]:
```
numerical_columns = df_original.select_dtypes( include = ['number']).columns

for col in numerical_columns:
    plt.figure( figsize = (8, 6))
    sns.histplot( df_original[col], kde = True, bins = 30 )
    plt.title( f'{col}' )
    plt.xlabel( col )
    plt.ylabel( 'Frequency' )
    plt.show()
```

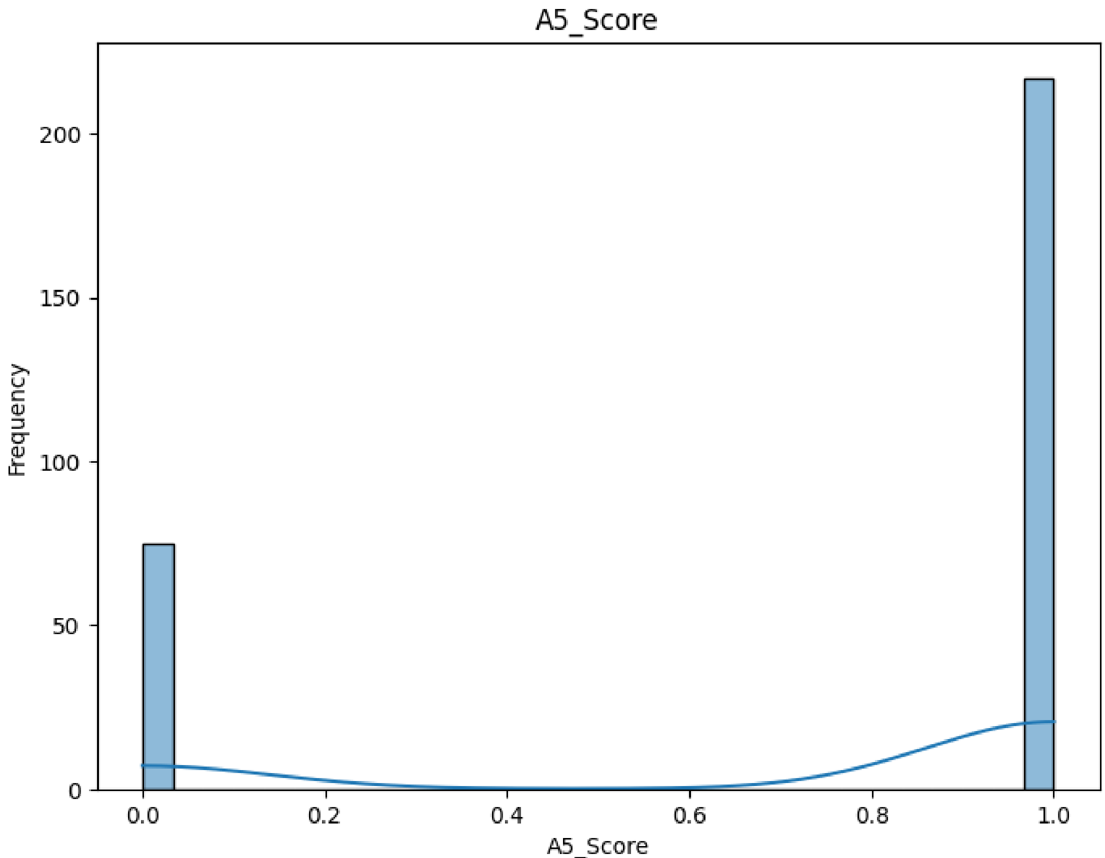


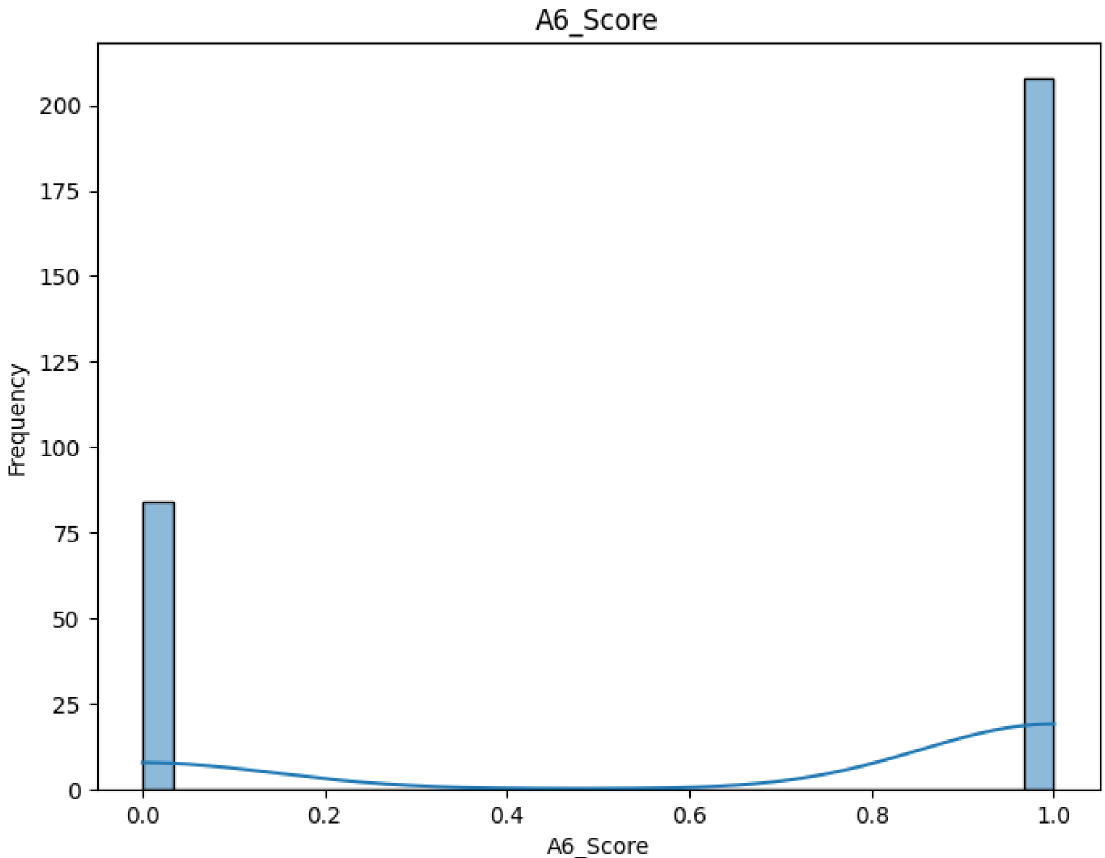
A1_Score
Frequency
175
150
125
100
75
50
25
0
0.0
0.2
0.4
0.6
0.8
1.0
A1_Score

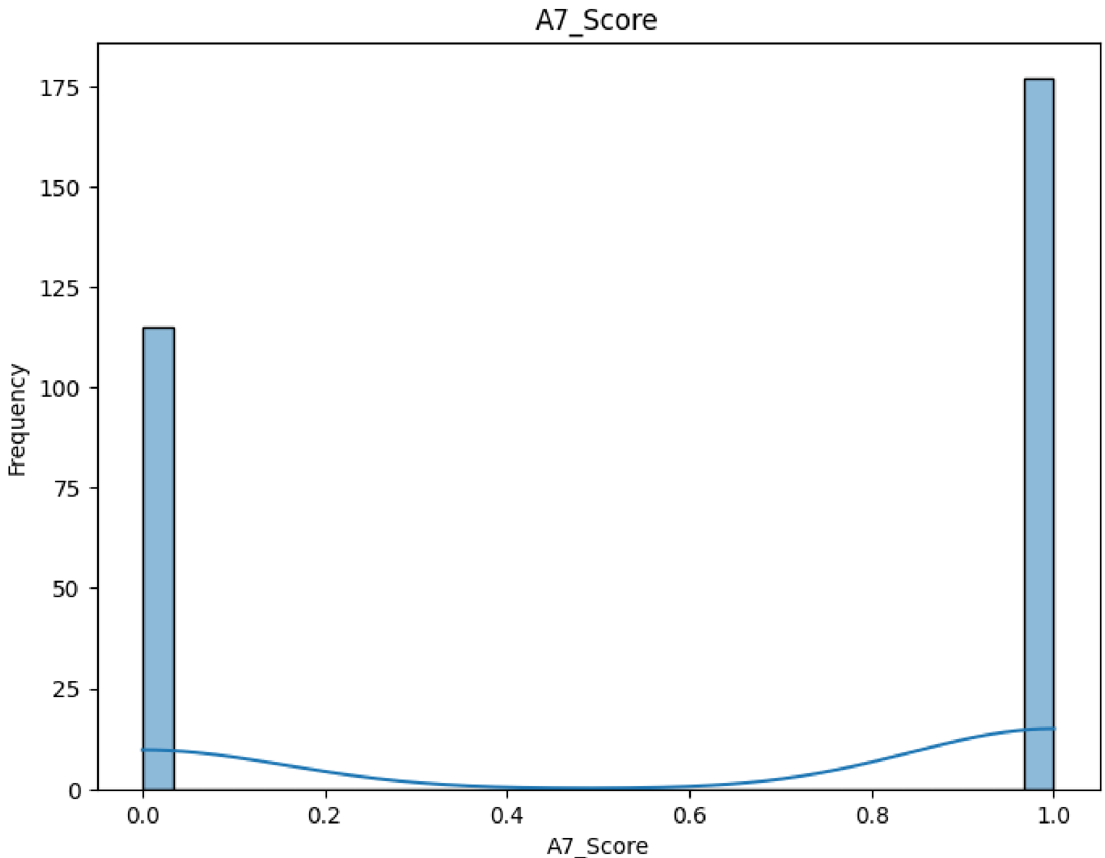

A2_Score
Frequency
A2_Score
0
20
40
60
80
100
120
140
160
0.0
0.2
0.4
0.6
0.8
1.0

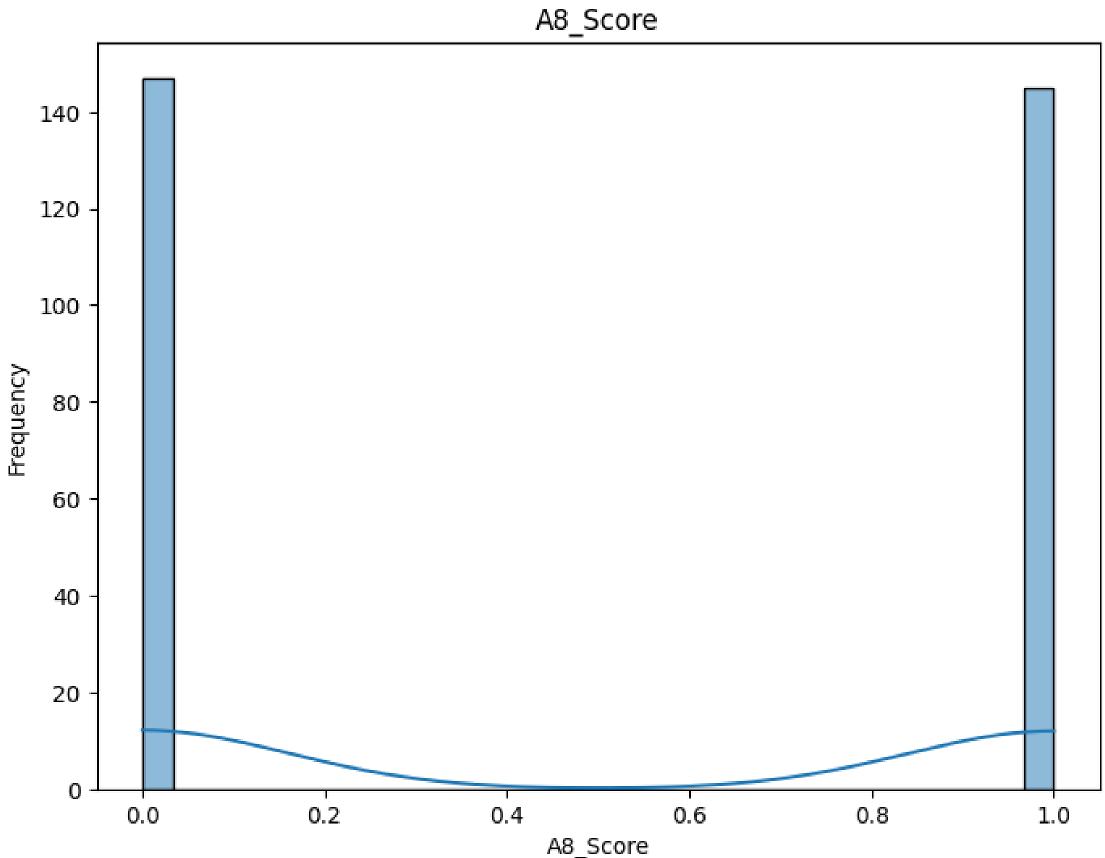

A3_Score
Frequency
A3_Score
0
50
100
150
200
0.0
0.2
0.4
0.6
0.8
1.0

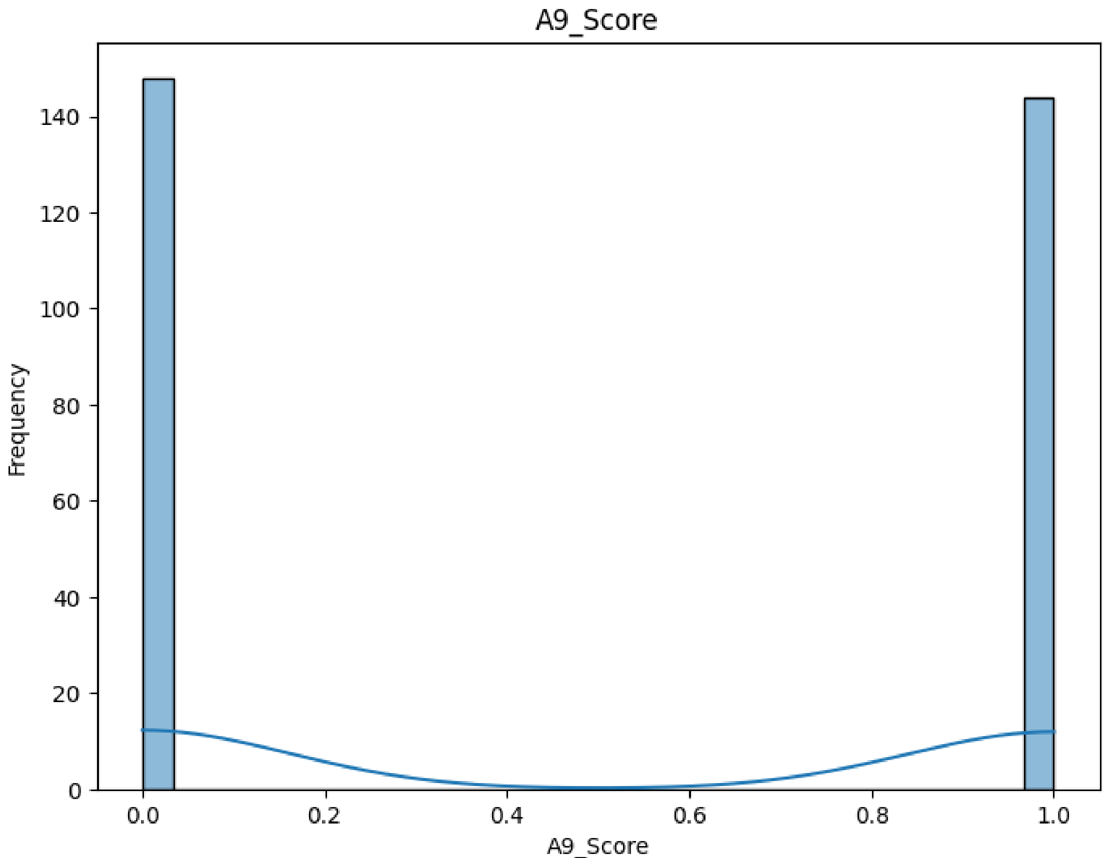

A4_Score
Frequency
A4_Score
0
20
40
60
80
100
120
140
160
0.0
0.2
0.4
0.6
0.8
1.0

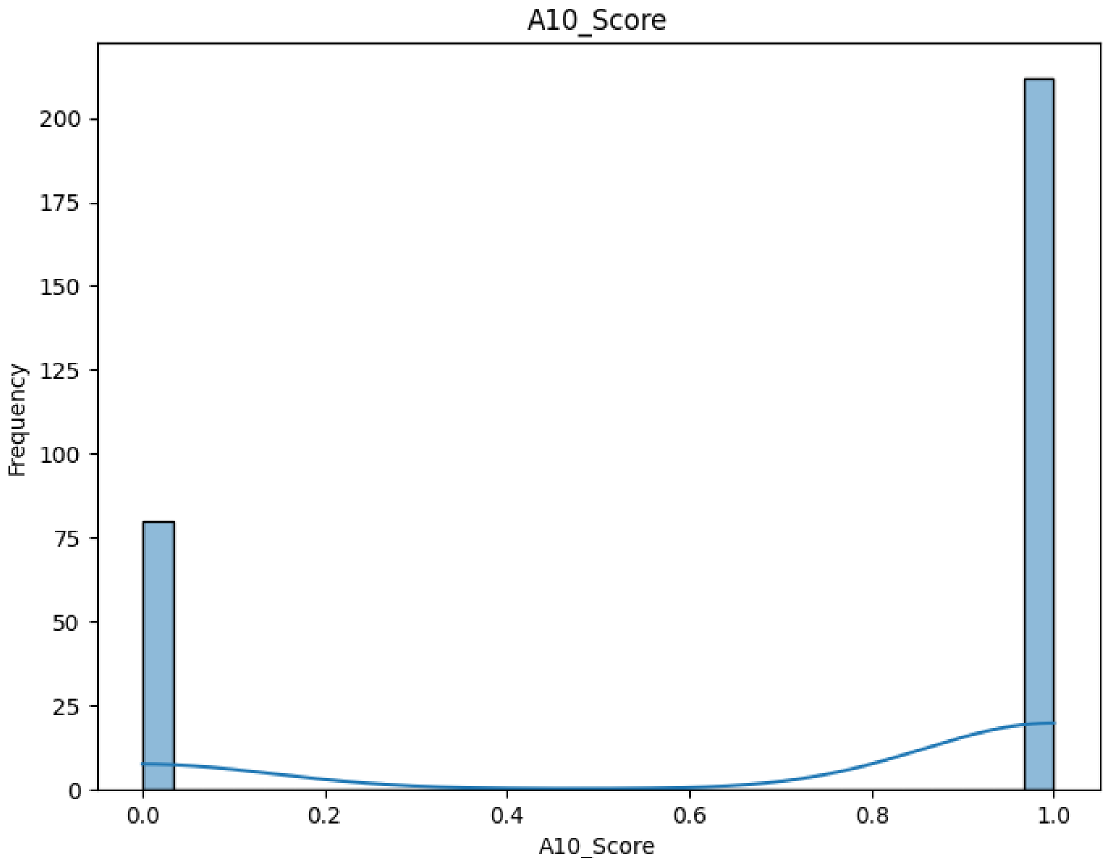

A5_Score
Frequency
200
150
100
50
0
0.0
0.2
0.4
0.6
0.8
1.0
A5_Score

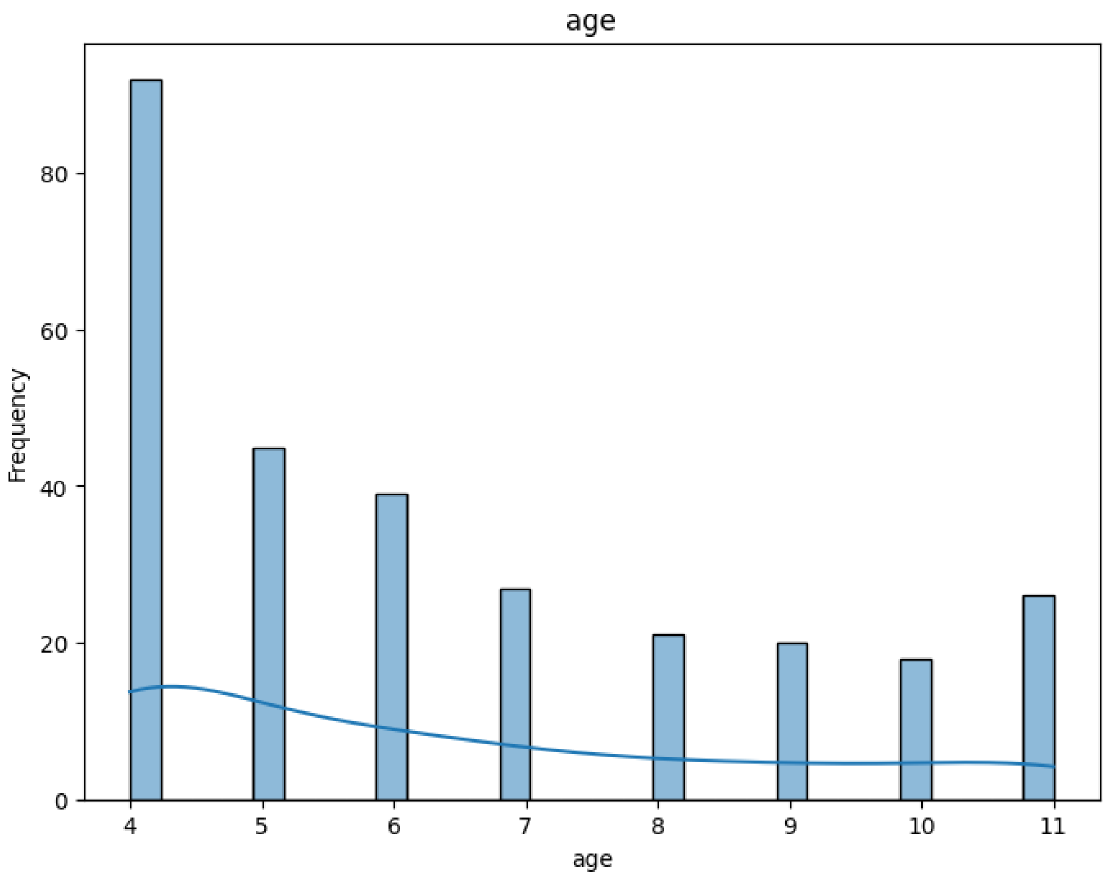

A6_Score
Frequency
200
175
150
125
100
75
50
25
0
0.0
0.2
0.4
0.6
0.8
1.0
A6_Score

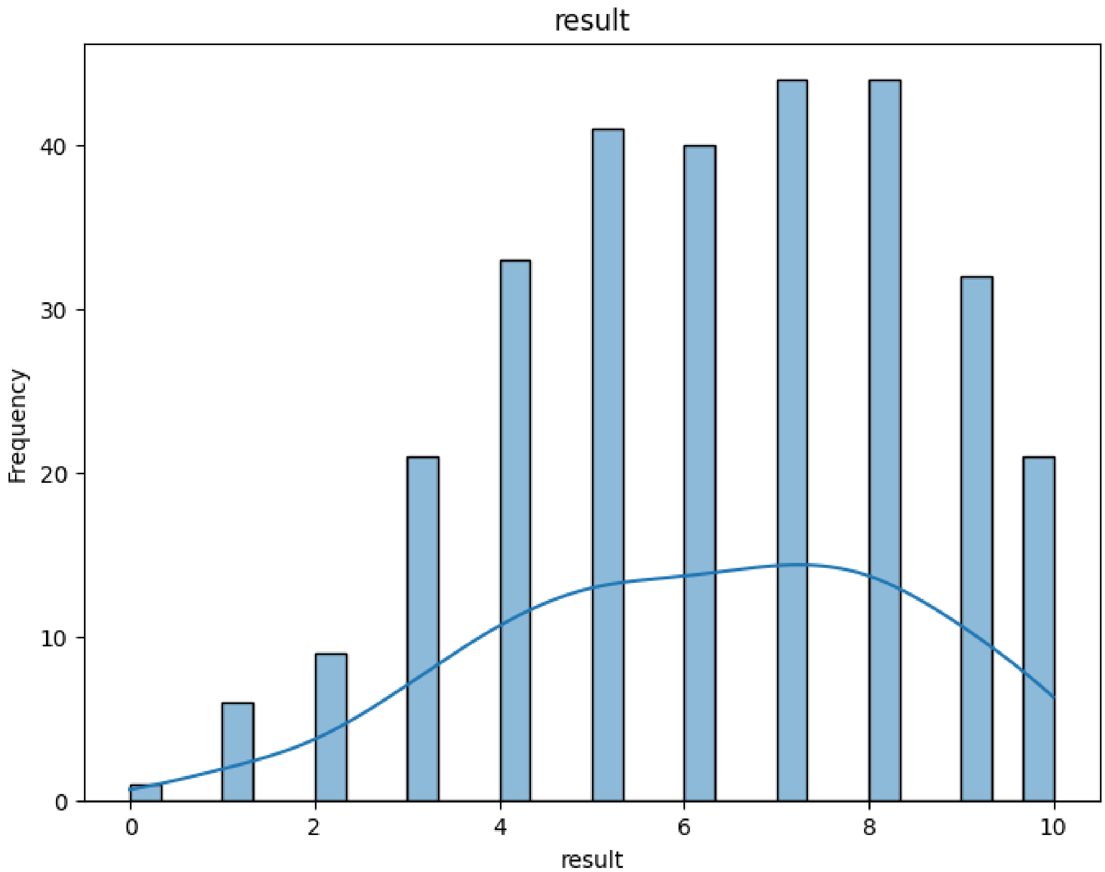

A7_Score
175
150
125
100
75
50
25
0
Frequency
0.0
0.2
0.4
0.6
0.8
1.0
A7_Score


A8_Score
140
120
100
80
60
40
20
0
Frequency
0.0
0.2
0.4
0.6
0.8
1.0
A8_Score


A9_Score
Frequency
A9_Score
0
20
40
60
80
100
120
140
0.0
0.2
0.4
0.6
0.8
1.0


A10_Score
Frequency
A10_Score
0
25
50
75
100
125
150
175
200
0.0
0.2
0.4
0.6
0.8
1.0

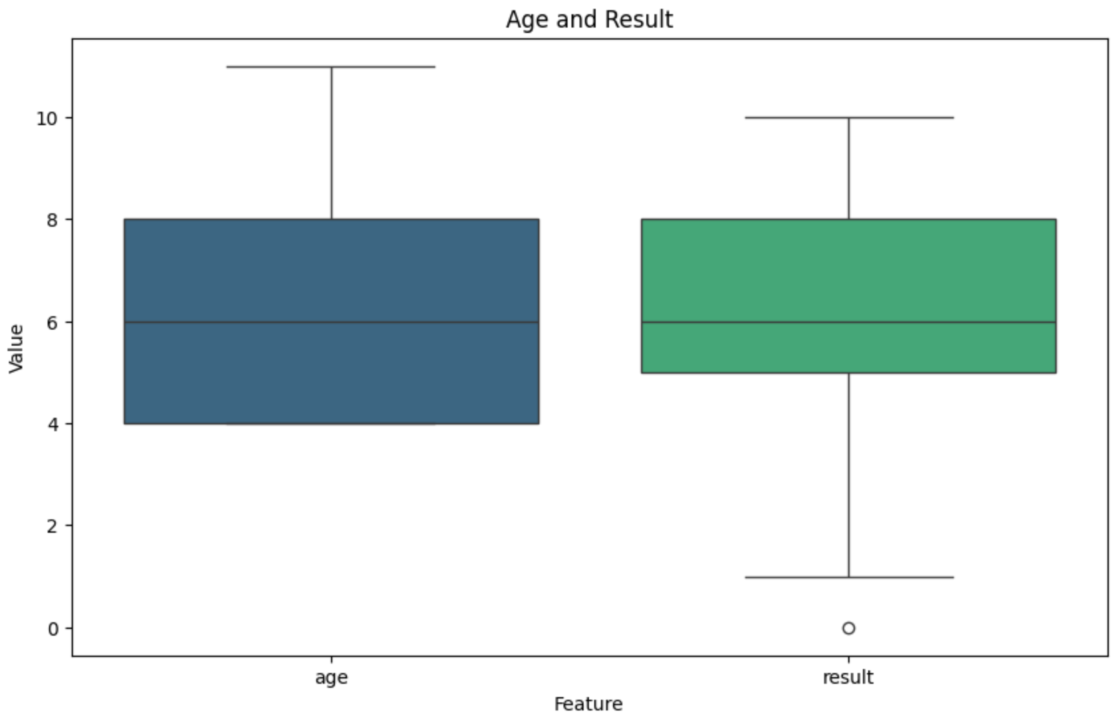

age
Frequency
0
20
40
60
80
4
5
6
7
8
9
10
11
age



1.5.4 Distribution for age and result features

- The **age** is centered around 6 years old.
- One outlier is observed for **result** feature and the result column is centered around 6 as the total score after answering the 10 questions.

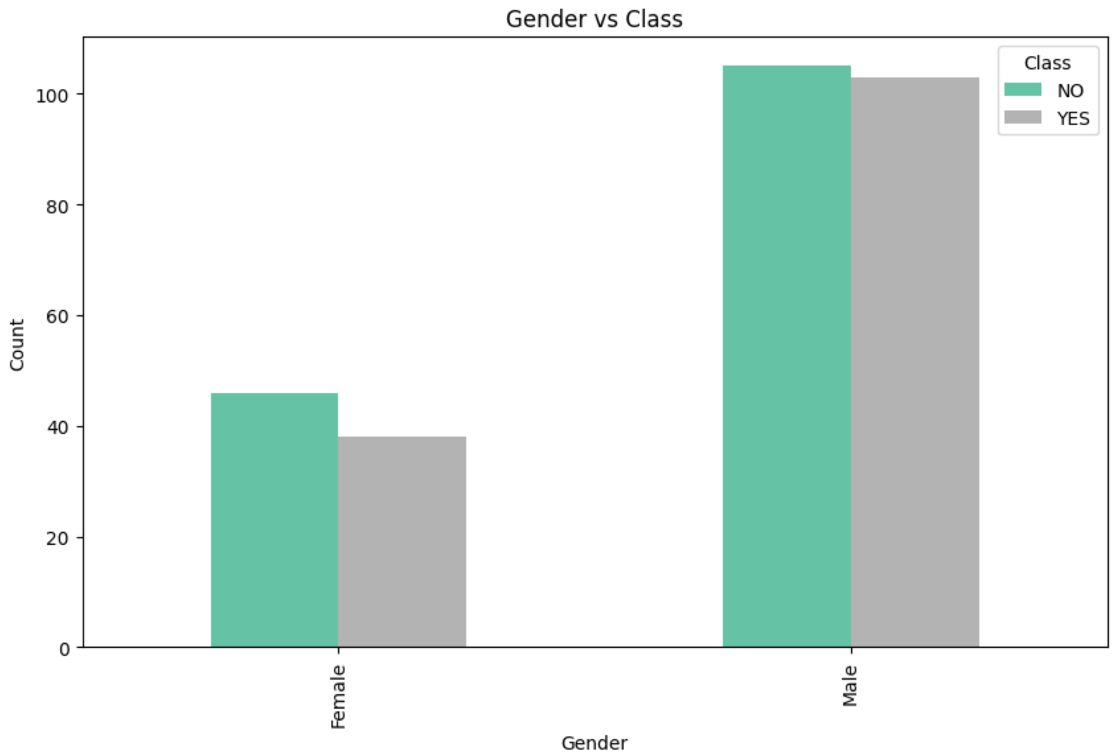
[25]:
```
columns_to_plot = ['age', 'result']
df_melted = df_original[columns_to_plot].melt( var_name = 'Feature', value_name␣
↪= 'Value' )

plt.figure( figsize = ( 10, 6 ) )
sns.boxplot( x = 'Feature', y = 'Value', data = df_melted, hue = 'Feature',␣
↪palette = 'viridis', dodge = False )
plt.title( 'Age and Result')
plt.xlabel( 'Feature' )
plt.ylabel( 'Value' )
plt.legend( [],[], frameon = False )
plt.show()
```



1.5.5 Gender and Class

- In the dataset we find slightly more **female** kids without autism than non autistic female kids.
- **Male** kids with autism are almost the same as those without autism.

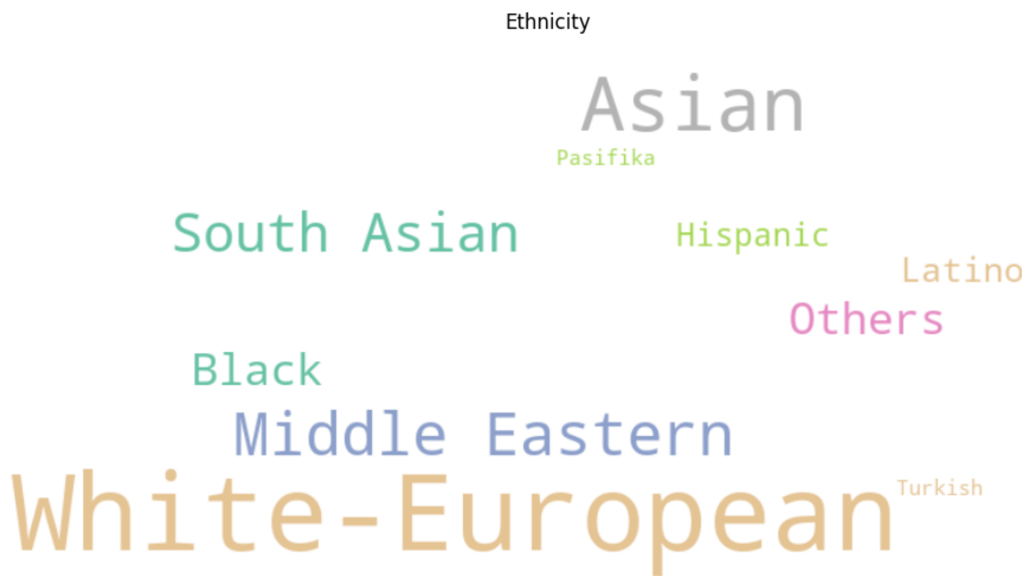
[26]:
```
df_original['gender'] = df_original['gender'].replace( {'m': 'Male', 'f':␣
↪'Female'} )

cross_tab = pd.crosstab( df_original['gender'], df_original['class'] )
cross_tab.plot( kind = 'bar', figsize = ( 10, 6 ), colormap = 'Set2' )
plt.title( 'Gender vs Class' )
plt.xlabel('Gender' )
plt.ylabel( 'Count' )
plt.legend( title = 'Class' )
plt.show()
```



1.5.6 Ethnicity Distribution

Most of the kids in the dataset are **White-European** followed by **Asian**, **Middle Eastern**, **South Asian**, and **Black**.

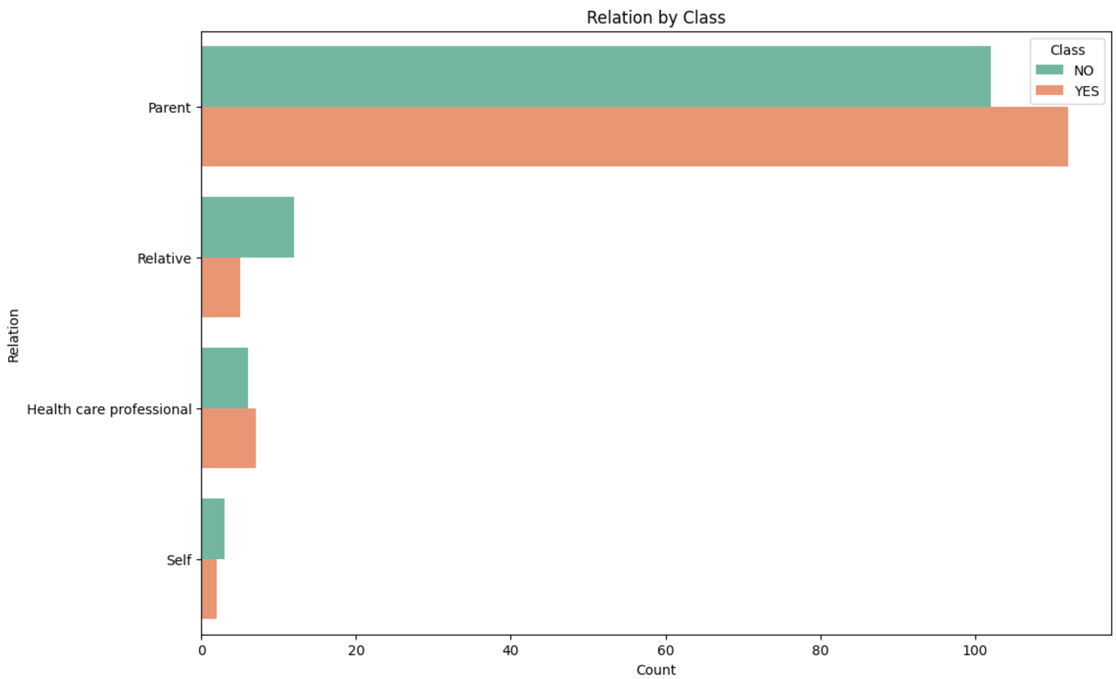
[27]:
```
df_original = clean_columns( df_original, columns_to_clean )
ethnicity_counts = df_original['ethnicity'].value_counts()

wordcloud = WordCloud( width = 800, height = 400, background_color = 'white',␣
↪colormap = 'Set2' ).generate_from_frequencies( ethnicity_counts )

plt.figure( figsize = ( 12, 8 ))
plt.imshow( wordcloud, interpolation = 'bilinear' )
plt.title( 'Ethnicity' )
plt.axis( 'off' )
plt.show()
```



1.5.7 Relation by Class

- The relation is the person who completed the test.
- For the **parent** category, the number of the autistic kids whom they completed the tests for is fairly higher than for the kids without autism.
- For the **relative** category, the number of the autistic kids who they completed the tests for is significantly lower than for the kids without autism.
- For the rest of the categories, the numbers are fairly close.

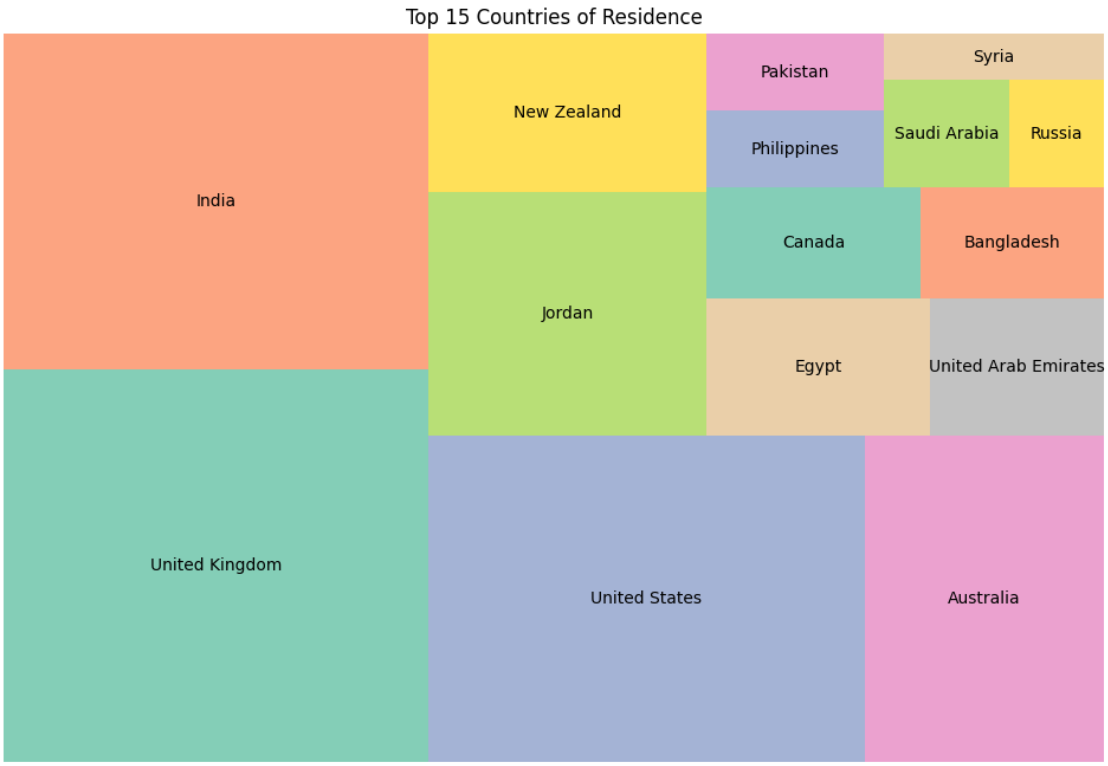
[28]:
```
df_original['relation'] = df_original['relation'].replace( {'self': 'Self',␣
↪'Self': 'Self'} )

plt.figure( figsize = ( 12, 8 ) )
sns.countplot( y = 'relation', data = df_original, palette = 'Set2', hue =␣
↪'class', order = df_original['relation'].value_counts().index )
plt.title( 'Relation by Class' )
plt.xlabel( 'Count' )
plt.ylabel( 'Relation' )
plt.legend( title='Class' )
plt.show()
```



1.5.8 Top 15 Countries of Residence

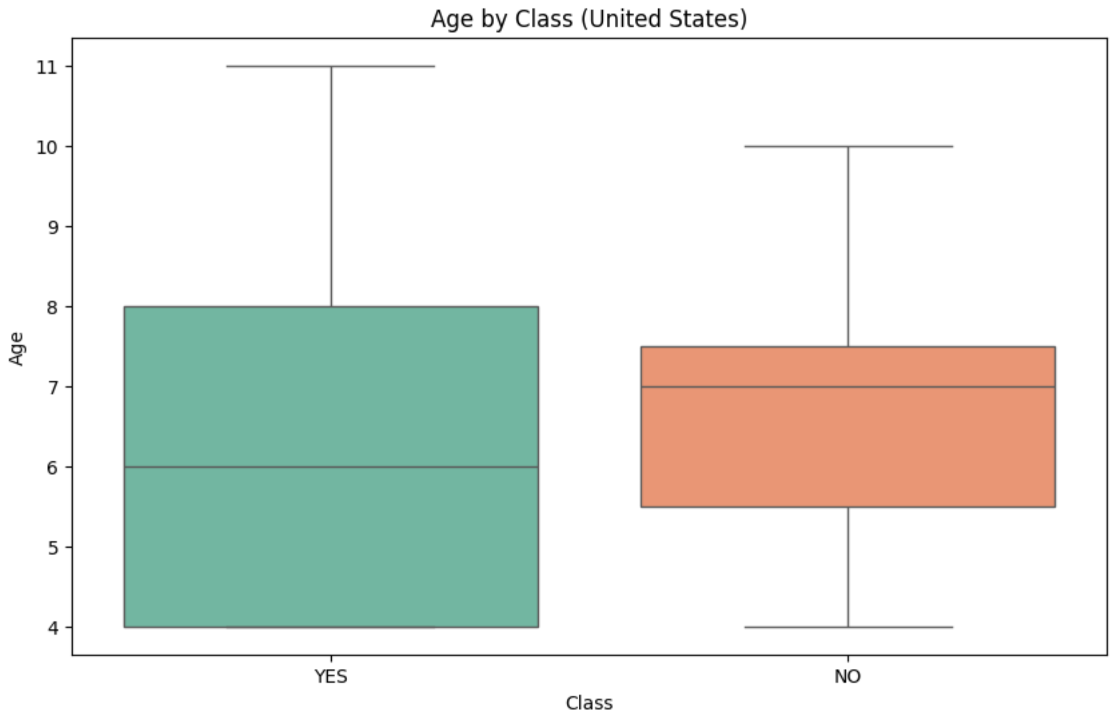
Most kids in the dataset are from **United Kingdom** and **India** followed by **United States**, **Australia**, **Jordan**, and **New Zealand**.

[29]:
```
top_15_countries = df_original['country_of_res'].value_counts().nlargest( 15 )

plt.figure( figsize = ( 12, 8 ) )
squarify.plot( sizes = top_15_countries.values, label = top_15_countries.index,␣
↪alpha = 0.8, color = sns.color_palette( 'Set2', len( top_15_countries  ) ) )
plt.title( 'Top 15 Countries of Residence' )
plt.axis( 'off' )
plt.show()
```



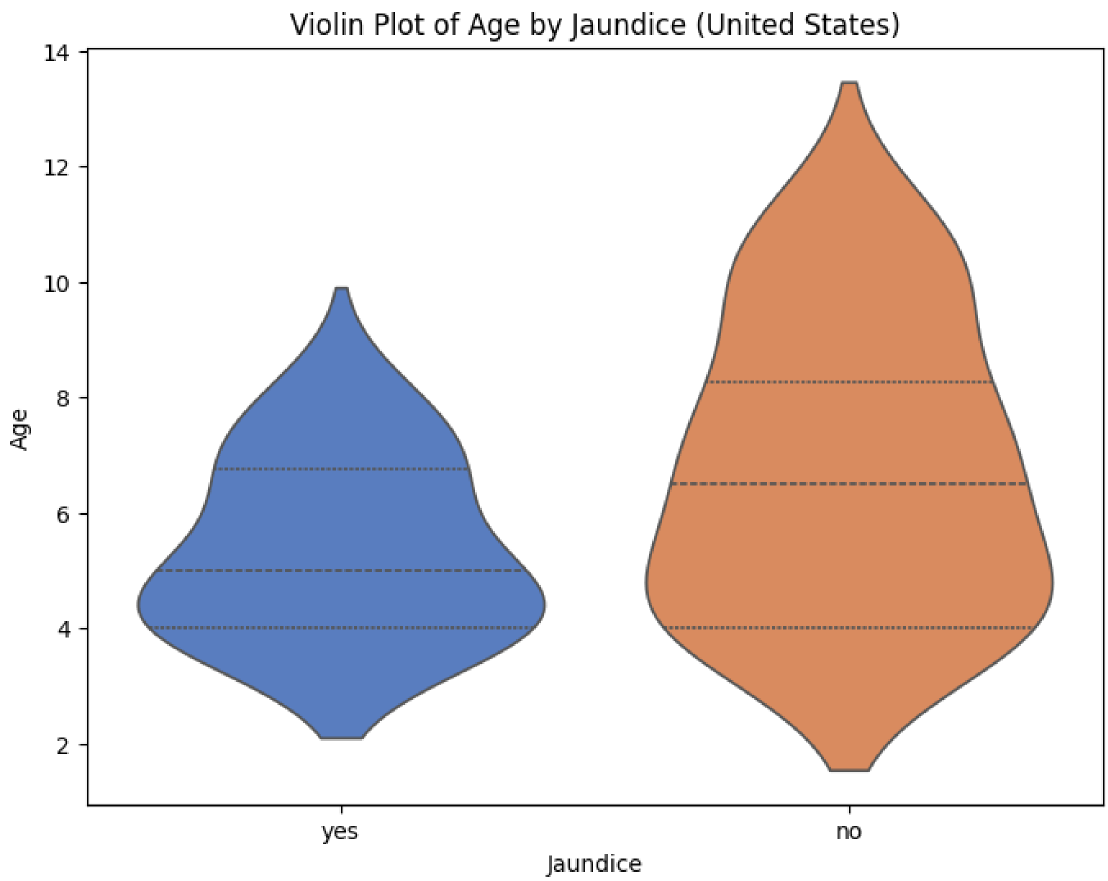
The kids in the dataset who are from the **United States**, most of them are autistic and the median age is 6 years old whereas for the kids who are not autistic, the median age is 7 years old.

[30]:
```
df_us = df_original[df_original["country_of_res"] == "United States"]

plt.figure( figsize = ( 10, 6 ) )
sns.boxplot( x = "class", y = "age", data = df_us, palette = "Set2", hue =␣
 ↪"class", dodge = False )
plt.title( "Age by Class (United States)" )
plt.xlabel( "Class" )
plt.ylabel( "Age" )
plt.show()
```



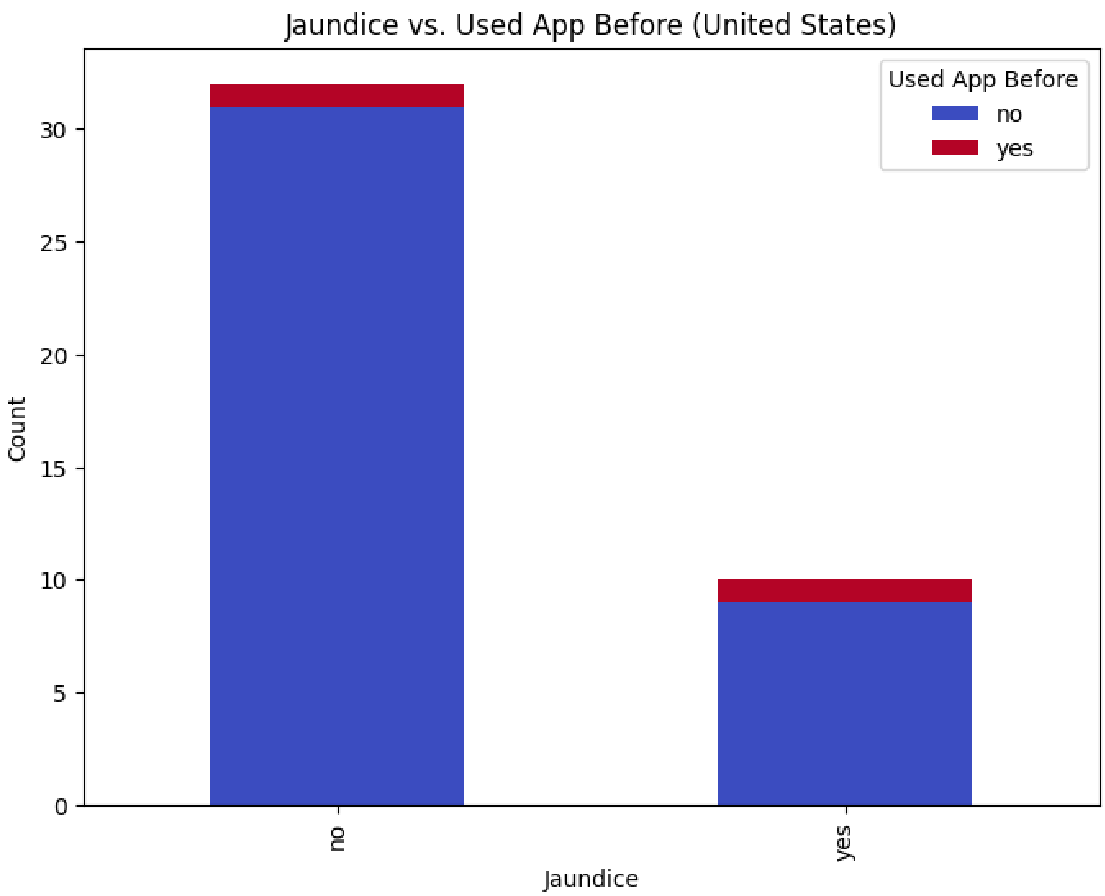
Children (**United States**) with jaundice tend to be younger, while those without jaundice have a wider age distribution with more older children.

[31]:
```
plt.figure( figsize = ( 8, 6 ) )
sns.violinplot( x = "jaundice", y = "age", data = df_us, palette = "muted",␣
↪inner = "quartile", hue = "jaundice", dodge = False )
plt.title( "Violin Plot of Age by Jaundice (United States)" )
plt.xlabel( "Jaundice" )
plt.ylabel( "Age" )
plt.show()
```



Most children (**United States**), regardless of jaundice status, have not used a screening app before, indicating no strong correlation between jaundice and app usage.

[32]:
```
jaundice_app_counts = pd.crosstab( df_us["jaundice"], df_us["used_app_before"] )
jaundice_app_counts.plot( kind = "bar", stacked = True, colormap = "coolwarm",␣
  ↪figsize = ( 8, 6 ) )
plt.title( "Jaundice vs. Used App Before (United States)" )
plt.xlabel( "Jaundice" )
plt.ylabel( "Count" )
plt.legend( title = "Used App Before" )
plt.show()
```

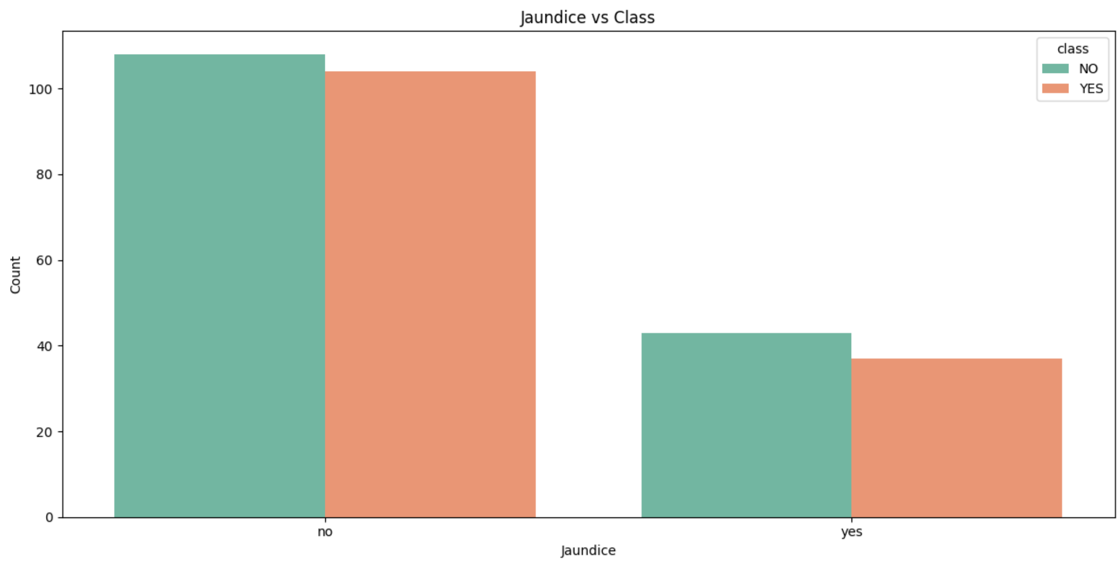


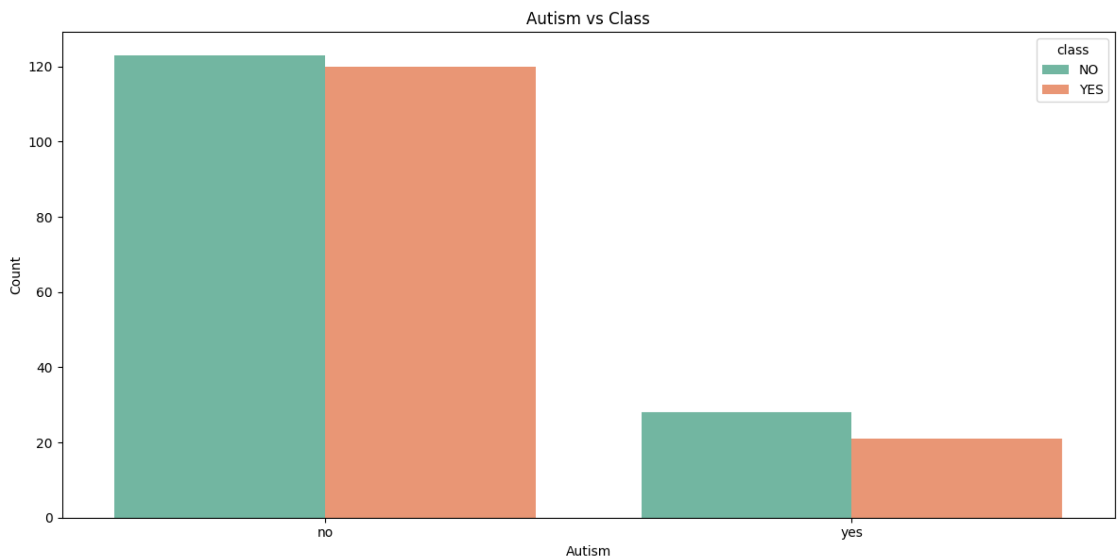
1.5.9 Comparing jaundice, autism, and used_app_before versus class

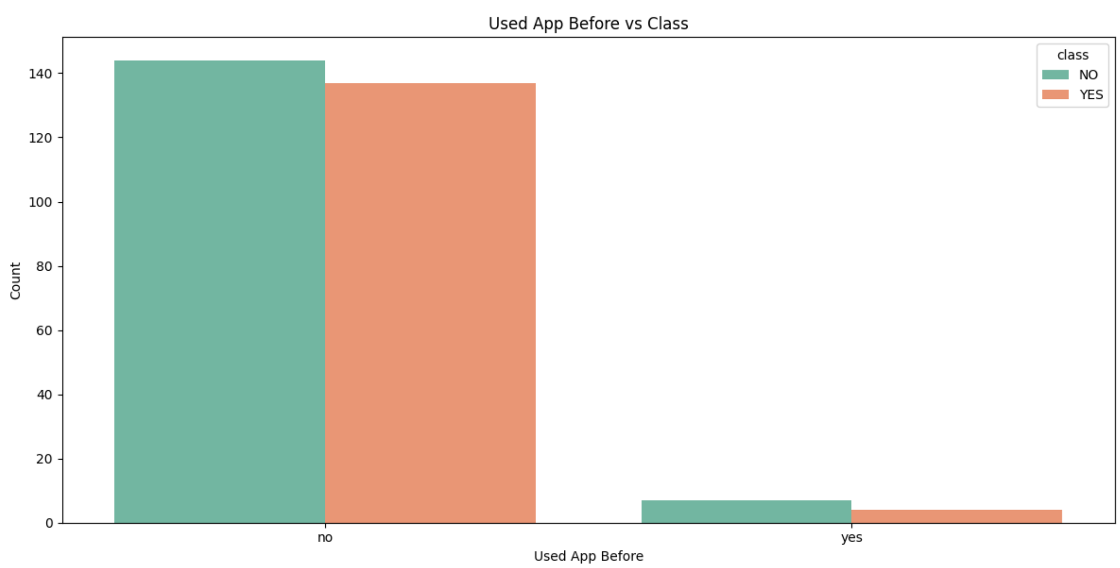
- Most of the kids in the dataset do not have **jaundice** but there's no clear relationship between jaundice and having or not having autism.
- **autism** column shows whether any immediate family member has a pervasive developmental disorder (PDD) (yes or no) and most kids in the dataset in the dataset do not have PDD. Also there's no clear relationship between PDD and having or not having autism.
- **used_app_before** column means whether the user has used a screening app before (yes or no) and most kids in the dataset do not. Also there's no clear relationship between using having a screening app before and having or not having autism.

[33]:
```
fig, axes = plt.subplots( 3, 1, figsize = ( 12, 18 ) )

sns.countplot( x = 'jaundice', hue = 'class', data = df_original, palette =␣
↪'Set2', ax = axes[0] )
axes[0].set_title( 'Jaundice vs Class' )
axes[0].set_xlabel( 'Jaundice' )
axes[0].set_ylabel( 'Count' )
```

```
sns.countplot(x = 'autism', hue = 'class', data = df_original, palette ='Set2',␣
↪ax = axes[1] )
axes[1].set_title( 'Autism vs Class' )
axes[1].set_xlabel( 'Autism' )
axes[1].set_ylabel( 'Count' )

sns.countplot( x = 'used_app_before', hue = 'class', data = df_original,␣
↪palette = 'Set2', ax = axes[2] )
axes[2].set_title( 'Used App Before vs Class' )
axes[2].set_xlabel( 'Used App Before' )
axes[2].set_ylabel( 'Count' )

plt.tight_layout()
plt.show()
```


Jaundice vs Class
Count
0
20
40
60
80
100
no
yes
Jaundice
class
NO
YES

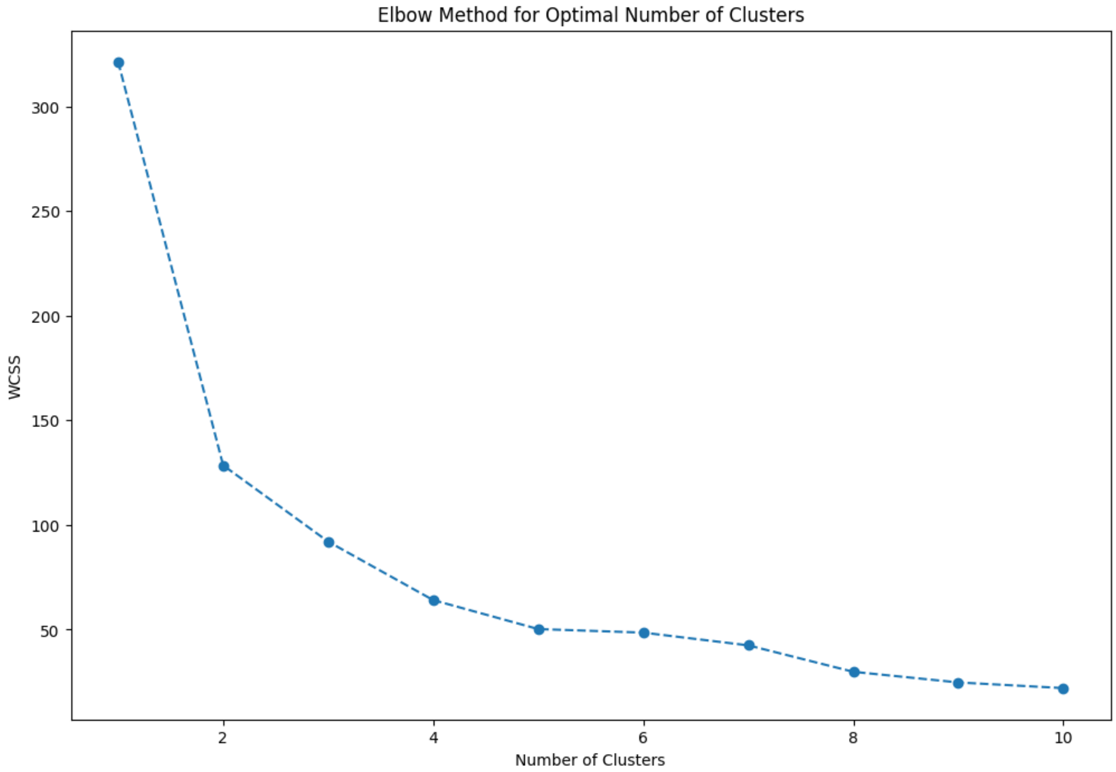

Autism vs Class
Count
0
20
40
60
80
100
120
no
yes
Autism
class
NO
YES


Used App Before vs Class
Count
0
20
40
60
80
100
120
140
no
yes
Used App Before
class
NO
YES

1.5.10 PCA and K-Means Clustering

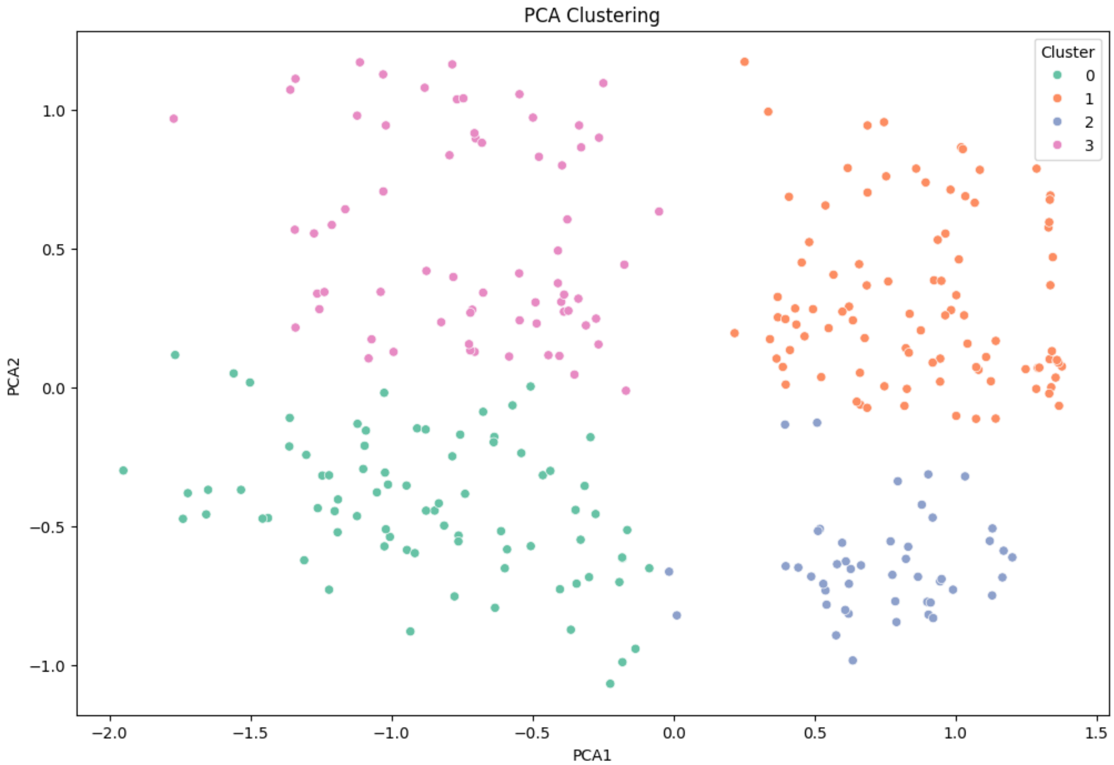
- **PCA** is utilized here to reduce the dataset to **2** principal components, followed by **K-Means** clustering
- The dataset shows **4** clusters that the dataset can be divided into.

[34]:
```
numerical_imputer = SimpleImputer( strategy = 'median' )
df_original[df_original.select_dtypes( include = ['number'] ).columns] =␣
 ↪numerical_imputer.fit_transform( df_original.select_dtypes( include =␣
 ↪['number'] ) )

df_original[df_original.select_dtypes( include = ['object', 'category']).
 ↪columns] = df_original.select_dtypes( include = ['object', 'category'] ).
 ↪fillna( 'Unknown' )

label_encoders = {}
for column in df_original.select_dtypes( include = ['object', 'category'] ).
 ↪columns:
    le = LabelEncoder()
    df_original[column] = le.fit_transform( df_original[column] )
    label_encoders[column] = le

scaler = MinMaxScaler()
scaled_data = scaler.fit_transform( df_original )

pca = PCA( n_components = 2 )
pca_data = pca.fit_transform( scaled_data )

wcss = []
for i in range( 1, 11 ):
    kmeans = KMeans( n_clusters = i, random_state = 42 )
    kmeans.fit( pca_data )
    wcss.append( kmeans.inertia_ )

plt.figure( figsize = ( 12, 8 ) )
plt.plot( range(1, 11), wcss, marker = 'o', linestyle = '--')
plt.title( 'Elbow Method for Optimal Number of Clusters' )
plt.xlabel( 'Number of Clusters' )
plt.ylabel( 'WCSS' )
plt.show()
```



[35]:

```
kmeans = KMeans( n_clusters = 4, random_state = 42 )
clusters = kmeans.fit_predict( pca_data )

df_pca = pd.DataFrame( pca_data, columns = ['PCA1', 'PCA2'] )
df_pca['Cluster'] = clusters

plt.figure( figsize = ( 12, 8 ) )
sns.scatterplot(x = 'PCA1', y = 'PCA2', hue = 'Cluster', palette = 'Set2', data␣
↪= df_pca )
plt.title( 'PCA Clustering' )
plt.xlabel( 'PCA1' )
plt.ylabel( 'PCA2' )
plt.legend( title = 'Cluster' )
plt.show()
```


PCA Clustering
Cluster
0
1
2
3
PCA1
PCA2
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
−1.0
−0.5
0.0
0.5
1.0