Autism Spectrum Disorder (ASD) prediction

Title: Autism Spectrum Disorder Prediction Using Machine Learning

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Abstract

Autism Spectrum Disorder (ASD) is a developmental condition affecting communication, behavior, and social skills. Early detection is critical for timely intervention. In this project, we explore the use of machine learning models—Logistic Regression, SVM, and Decision Trees—to predict ASD using patient health, behavioral, and demographic data. After thorough data preprocessing and visualization, we trained the models and evaluated them using ROC-AUC scores and confusion matrices. The models showed excellent performance, enabling reliable classification of ASD traits.

Introduction

ASD affects millions of children globally and varies in severity. Early screening can significantly improve quality of life through interventions. Traditionally, diagnosis requires clinical assessments, but with the availability of structured medical and behavioral data, machine learning offers promising tools for scalable, data-driven screening.

This project leverages a dataset containing 1985 entries with features including questionnaire scores, family history, ethnicity, age, and medical background. Using Python libraries like pandas, seaborn, and scikit-learn, we conducted extensive EDA, applied transformations, engineered features, and tested various classifiers to detect ASD traits.

Problem Statement

To develop a machine learning-based solution that can predict whether a child shows ASD traits based on demographic, behavioral, and clinical indicators.

Objectives

- Perform exploratory data analysis on ASD-related data
- Preprocess and transform features for effective learning
- Build classification models to predict ASD traits
- Evaluate models using ROC-AUC and confusion matrix
- Provide insights for early diagnosis and intervention

Data Sources

- Dataset: CSV file provided for DWDA mini project (1985 records, 28 features)
- Fields: Questionnaire (A1–A10), Age, Sex, Ethnicity, ASD traits, and medical/family history

Methodology

Data Preprocessing

- Removed outliers based on Qchat_10_Score
- Converted categorical values (yes/no) to binary (1/0)
- Filled missing values and standardized numerical fields using StandardScaler
- Encoded categorical columns with LabelEncoder
- Used RandomOverSampler to balance class distribution

Feature Engineering

- Created sum_score from A1–A9 (indicating behavioral score)
- Added 'ind' column to represent cumulative risk from jaundice and family history
- Age converted to age groups (Toddler, Kid, Teenager, etc.)

Visualization

- Count plots of categorical columns against ASD traits
- Box plots and distribution plots of continuous variables
- Heatmap for feature correlation (correlation > 0.8 shown)

Modeling

- Models used:
    - Logistic Regression
    - Support Vector Machine (SVM)

    - Decision Tree Classifier
- Target variable: ASD_traits
- Features: All other columns excluding patient ID

Evaluation Metrics

- ROC-AUC Score
- Confusion Matrix
- Visual plots of model prediction performance

dwda-mini-project

April 5, 2025

[3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn import metrics
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import RandomOverSampler

import warnings
warnings.filterwarnings('ignore')
```

[4]:
```
df = pd.read_csv('C:\\Users\\Shree\\OneDrive\\Desktop\\DWDA\\MINI_PROJECT_DS.
↪csv')
print(df.head())
```

```
   CASE_NO_PATIENT'S  A1  A2  A3  A4  A5  A6  A7  A8  A9  …  \
0                  1   0   0   0   0   0   0   1   1   0  …
1                  2   1   1   0   0   0   1   1   0   0  …
2                  3   1   0   0   0   0   0   1   1   0  …
3                  4   1   1   1   1   1   1   1   1   1  …
4                  5   1   1   0   1   1   1   1   1   1  …

   Global developmental delay/intellectual disability  \
0                                                Yes
1                                                Yes
2                                                Yes
3                                                Yes
4                                                Yes

  Social/Behavioural Issues  Childhood Autism Rating Scale  Anxiety_disorder  \
0                       Yes                             1               Yes
1                       Yes                             2               Yes
2                       Yes                             4               Yes
3                       Yes                             2               Yes
4                       Yes                             1               Yes
```

```
  Sex       Ethnicity Jaundice Family_mem_with_ASD Who_completed_the_test  \
0   F  middle eastern      Yes                  No          Family Member
1   M  White European      Yes                  No          Family Member
2   M  Middle Eastern      Yes                  No          Family Member
3   M        Hispanic       No                  No          Family Member
4   F  White European       No                  No          Family Member

  ASD_traits
0         No
1        Yes
2        Yes
3        Yes
4        Yes

[5 rows x 28 columns]
```

[5]:
```
df.shape
```

[5]:
```
(1985, 28)
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1985 entries, 0 to 1984
Data columns (total 28 columns):
 #   Column                                              Non-Null Count  Dtype
---  ------                                              --------------  -----
 0   CASE_NO_PATIENT'S                                   1985 non-null   int64
 1   A1                                                  1985 non-null   int64
 2   A2                                                  1985 non-null   int64
 3   A3                                                  1985 non-null   int64
 4   A4                                                  1985 non-null   int64
 5   A5                                                  1985 non-null   int64
 6   A6                                                  1985 non-null   int64
 7   A7                                                  1985 non-null   int64
 8   A8                                                  1985 non-null   int64
 9   A9                                                  1985 non-null   int64
 10  A10_Autism_Spectrum_Quotient                        1985 non-null   int64
 11  Social_Responsiveness_Scale                         1982 non-null   object
 12  Age_Years                                           1985 non-null   int64
 13  Qchat_10_Score                                      1946 non-null   float64
 14  Speech Delay/Language Disorder                      1985 non-null   object
 15  Learning disorder                                   1985 non-null   object
 16  Genetic_Disorders                                   1985 non-null   object
 17  Depression                                          1984 non-null   object
 18  Global developmental delay/intellectual disability  1985 non-null   object
 19  Social/Behavioural Issues                           1971 non-null   object
```

```
 20  Childhood Autism Rating Scale                      1985 non-null   int64
 21  Anxiety_disorder                                   1985 non-null   object
 22  Sex                                                1985 non-null   object
 23  Ethnicity                                          1985 non-null   object
 24  Jaundice                                           1985 non-null   object
 25  Family_mem_with_ASD                                1985 non-null   object
 26  Who_completed_the_test                             1985 non-null   object
 27  ASD_traits                                         1985 non-null   object
dtypes: float64(1), int64(13), object(14)
memory usage: 434.3+ KB
```

[13]:
```
df.describe().T
```

[13]:

	count	mean	std	min	25%	50%	75%	max
CASE_NO_PATIENT'S	1985.0	993.000000	573.164462	1.0	497.0	993.0	1489.0	1985.0
A1	1985.0	0.299244	0.458042	0.0	0.0	0.0	1.0	1.0
A2	1985.0	0.238287	0.426143	0.0	0.0	0.0	0.0	1.0
A3	1985.0	0.213098	0.409600	0.0	0.0	0.0	0.0	1.0
A4	1985.0	0.272040	0.445123	0.0	0.0	0.0	1.0	1.0
A5	1985.0	0.278589	0.448418	0.0	0.0	0.0	1.0	1.0
A6	1985.0	0.306297	0.461071	0.0	0.0	0.0	1.0	1.0
A7	1985.0	0.345088	0.475517	0.0	0.0	0.0	1.0	1.0
A8	1985.0	0.243829	0.429499	0.0	0.0	0.0	0.0	1.0
A9	1985.0	0.259950	0.438717	0.0	0.0	0.0	1.0	1.0
A10_Autism_Spectrum_Quotient	1985.0	0.446348	0.497238	0.0	0.0	0.0	1.0	1.0
Age_Years	1985.0	9.624685	4.302416	1.0	7.0	9.0	14.0	18.0
Qchat_10_Score	1946.0	4.234841	2.898247	0.0	2.0	4.0	6.0	10.0
Childhood Autism Rating Scale	1985.0	1.701763	1.015367	1.0	1.0	1.0	2.0	4.0

[15]:
```
df['Ethnicity'].value_counts()
```

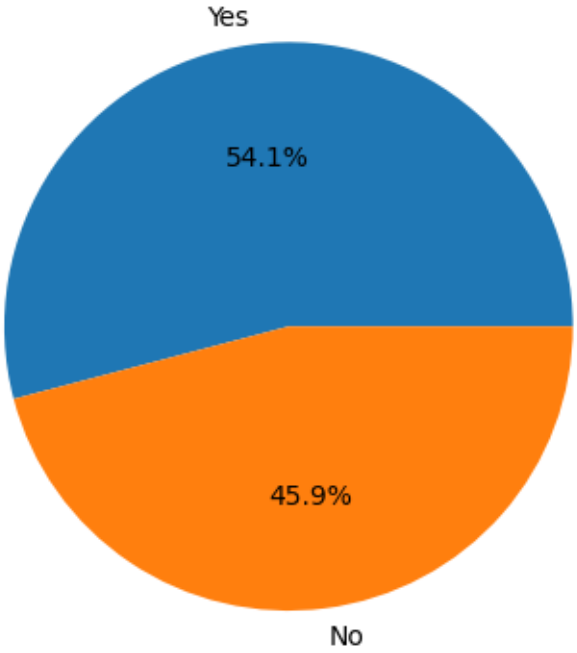
[15]:
```
Ethnicity
White European    549
Asian             392
Middle Eastern    362
asian             213
south asian       206
South Asian        49
Black              45
middle eastern     41
Hispanic           40
Others             35
Latino             26
black               8
PaciFica            8
Mixed               7
Native Indian       3
mixed               1
Name: count, dtype: int64
```

[17]:
```
df['Who_completed_the_test'].value_counts()
```

[17]:
```
Who_completed_the_test
Health Care Professional    1233
Family Member                658
Family member                 58
School and NGO                29
Self                           4
Others                         3
Name: count, dtype: int64
```

[19]:
```
df = df.replace({'yes':1, 'no':0, '?':'Others', 'others':'Others'})
```

[21]:
```
plt.pie(df['ASD_traits'].value_counts().values, labels=df['ASD_traits'].
 ↪value_counts().index, autopct='%1.1f%%')
plt.show()
```

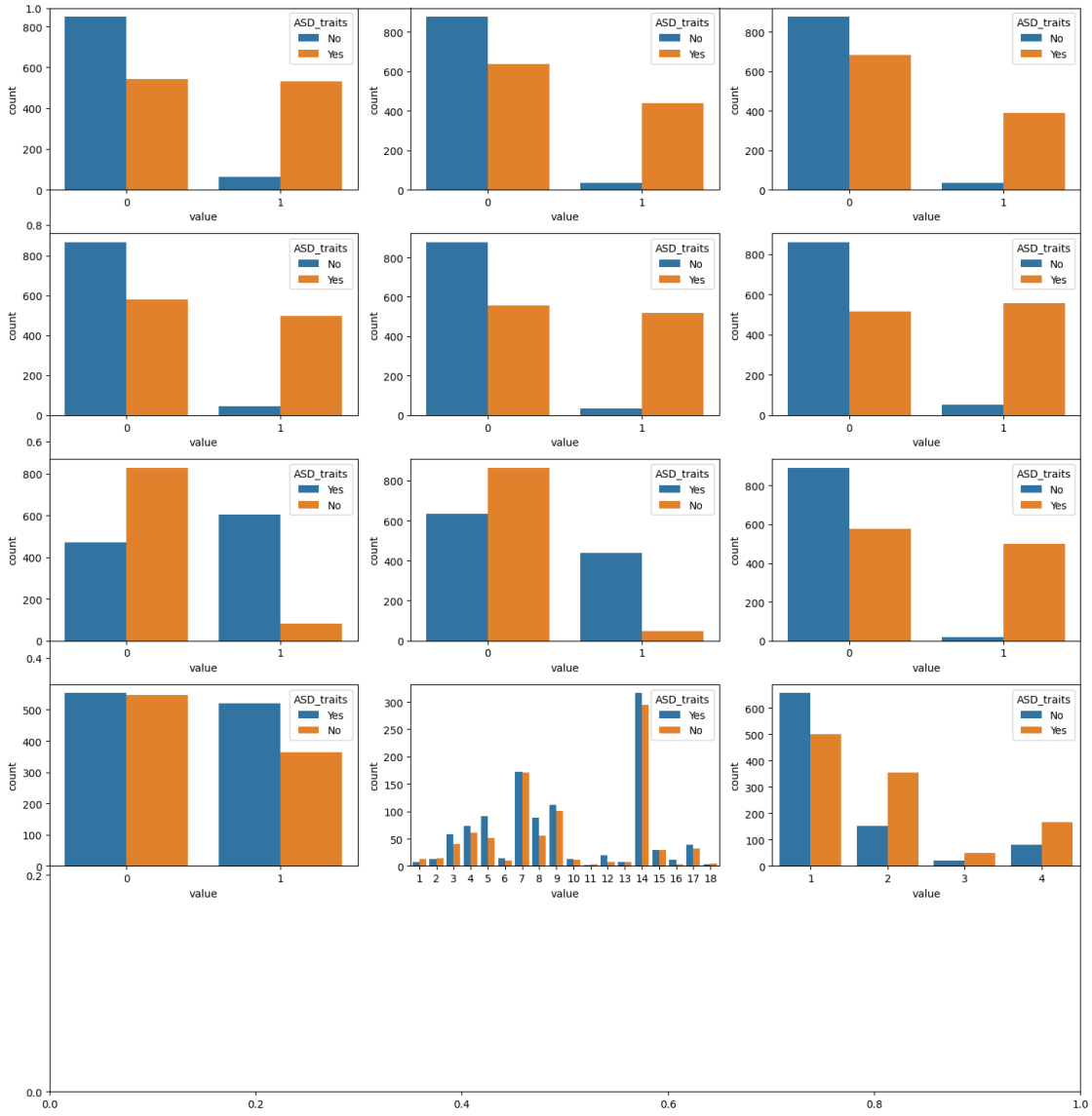


[23]:
```
ints = []
objects = []
floats = []

for col in df.columns:
    if df[col].dtype == np.int64:
        ints.append(col)
    elif df[col].dtype == object:
        objects.append(col)
    elif df[col].dtype == np.float64:
        floats.append(col)

if "CASE_NO_PATIENT'S" in ints:
    ints.remove("CASE_NO_PATIENT'S")

if 'ASD_traits' in objects:
    objects.remove('ASD_traits')

print("Ints:", ints)
print("Objects:", objects)
print("Floats:", floats)
```

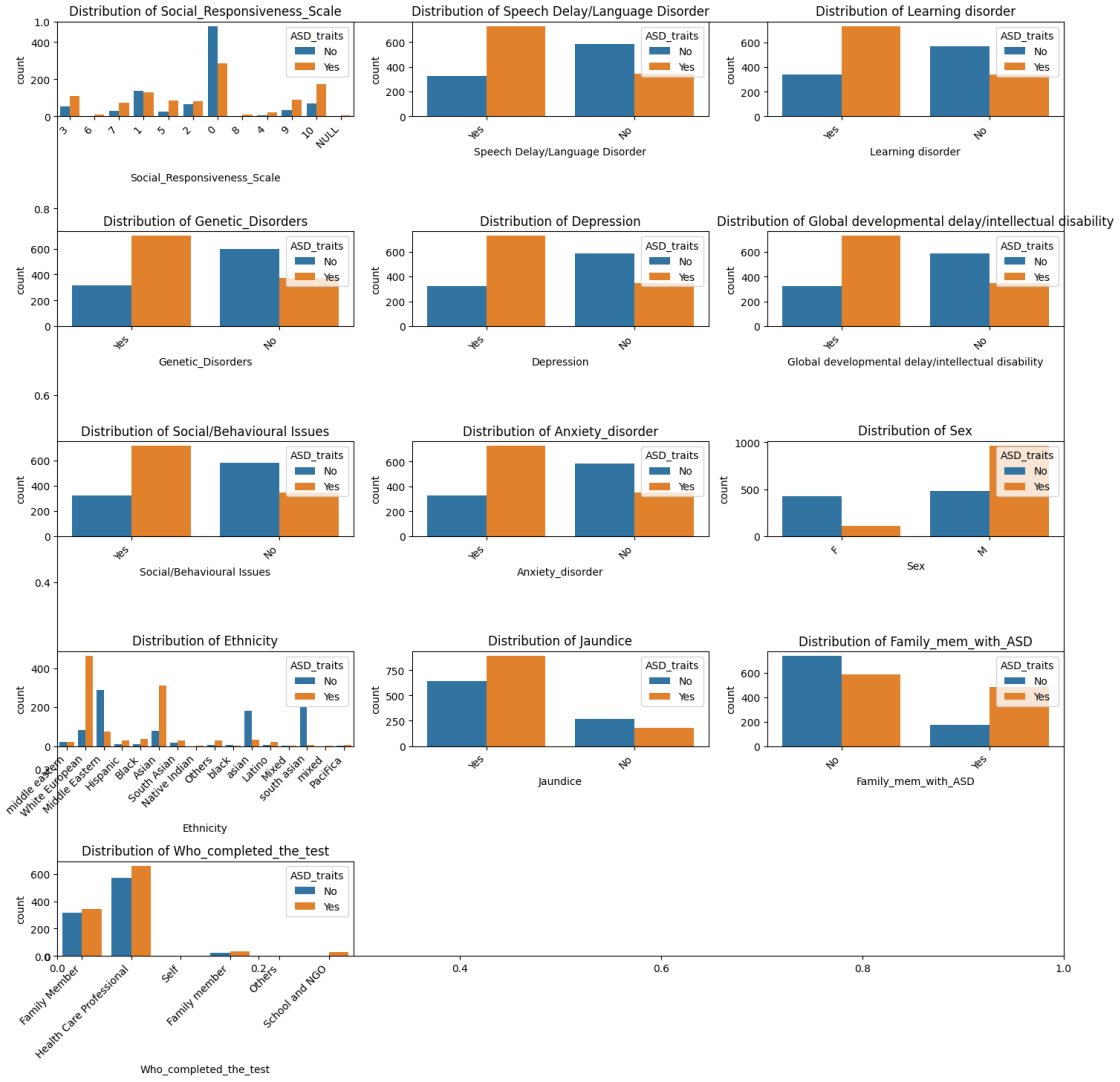
```
Ints: ['A1', 'A2', 'A3', 'A4', 'A5', 'A6', 'A7', 'A8', 'A9',
'A10_Autism_Spectrum_Quotient', 'Age_Years', 'Childhood Autism Rating Scale']
```

```
Objects: ['Social_Responsiveness_Scale', 'Speech Delay/Language Disorder',
'Learning disorder', 'Genetic_Disorders', 'Depression', 'Global developmental
delay/intellectual disability', 'Social/Behavioural Issues', 'Anxiety_disorder',
'Sex', 'Ethnicity', 'Jaundice', 'Family_mem_with_ASD', 'Who_completed_the_test']
Floats: ['Qchat_10_Score']
```

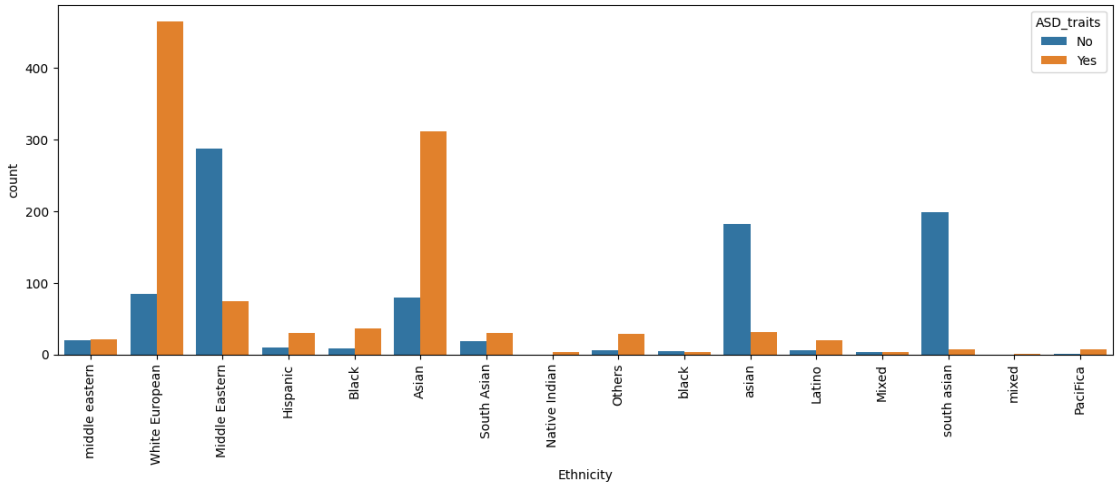
[25]:
```
# Convert the data to long-form using melt
df_melted = df.melt(id_vars=["CASE_NO_PATIENT'S", 'ASD_traits'],␣
 ↪value_vars=ints, var_name='col', value_name='value')

plt.subplots(figsize=(15,15))

for i, col in enumerate(ints):
  plt.subplot(5,3,i+1)
  # Use the melted DataFrame and specify x and hue
  sb.countplot(x='value', hue='ASD_traits', data=df_melted[df_melted['col'] ==␣
 ↪col])

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



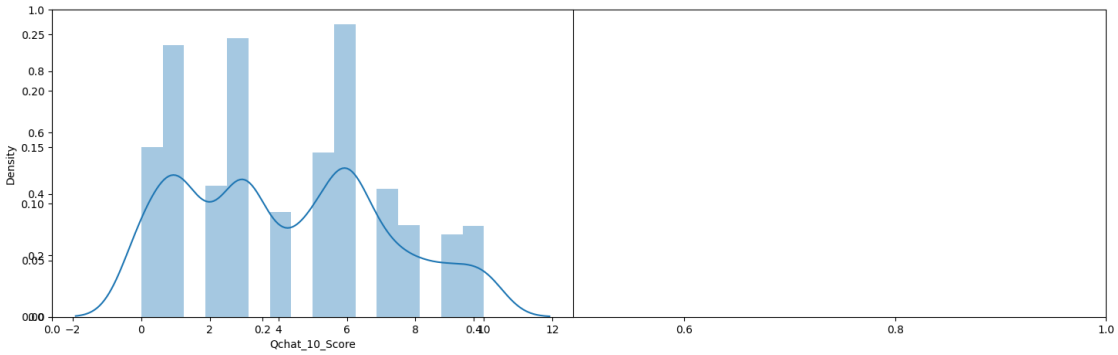
[27]:
```
plt.subplots(figsize=(15, 15))  # Adjust figure size as needed

for i, col in enumerate(objects):
    plt.subplot(5, 3, i + 1)  # Adjust subplot grid as needed
    sb.countplot(x=col, hue='ASD_traits', data=df)
    plt.title(f'Distribution of {col}')
    plt.xticks(rotation=45, ha='right') # Rotates x-axis labels for better
 ↪readability

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



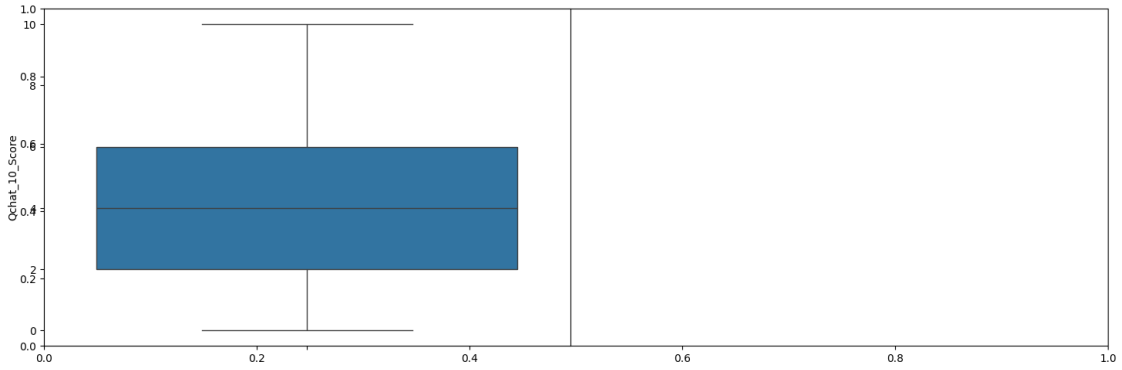
[31]:
```
plt.figure(figsize=(15,5))
sb.countplot(data=df, x='Ethnicity', hue='ASD_traits')
plt.xticks(rotation=90)
plt.show()
```



[33]:
```
plt.subplots(figsize=(15,5))

for i, col in enumerate(floats):
  plt.subplot(1,2,i+1)
  sb.distplot(df[col])
plt.tight_layout()
plt.show()
```



[35]:
```
plt.subplots(figsize=(15,5))

for i, col in enumerate(floats):
  plt.subplot(1,2,i+1)
  sb.boxplot(df[col])
plt.tight_layout()
plt.show()
```

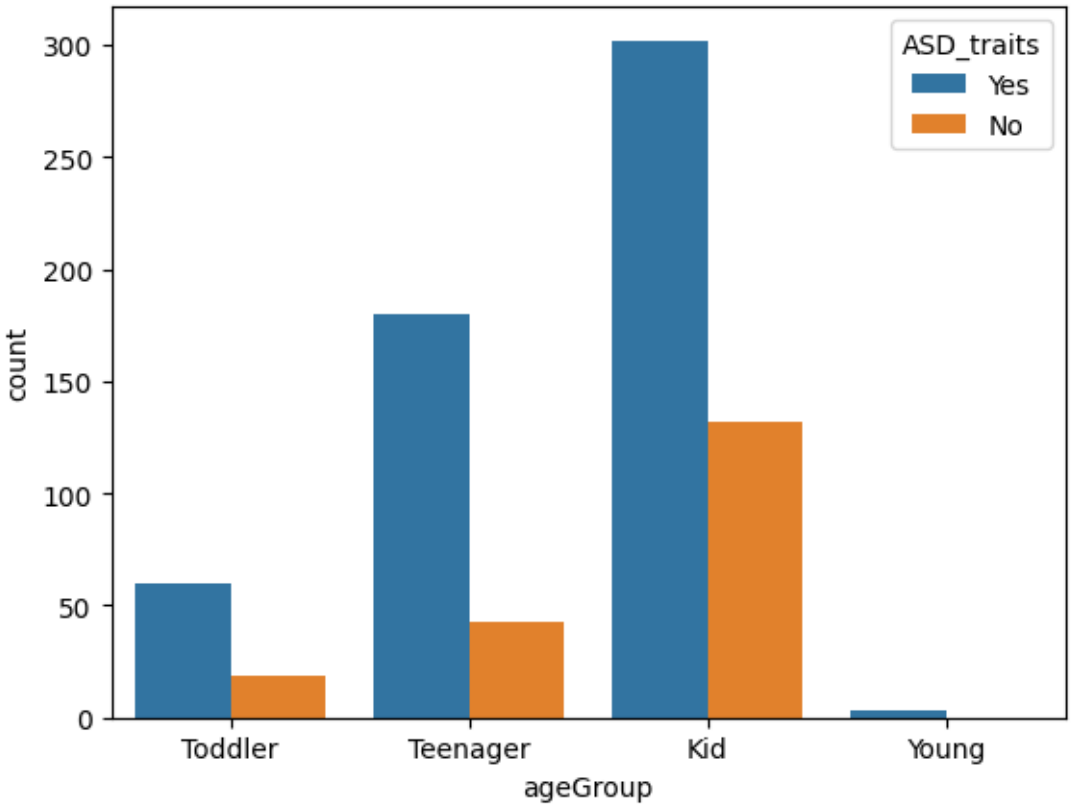


[43]:
```
df = df[df['Qchat_10_Score'] > 5]
df.shape
```

[43]: (739, 28)

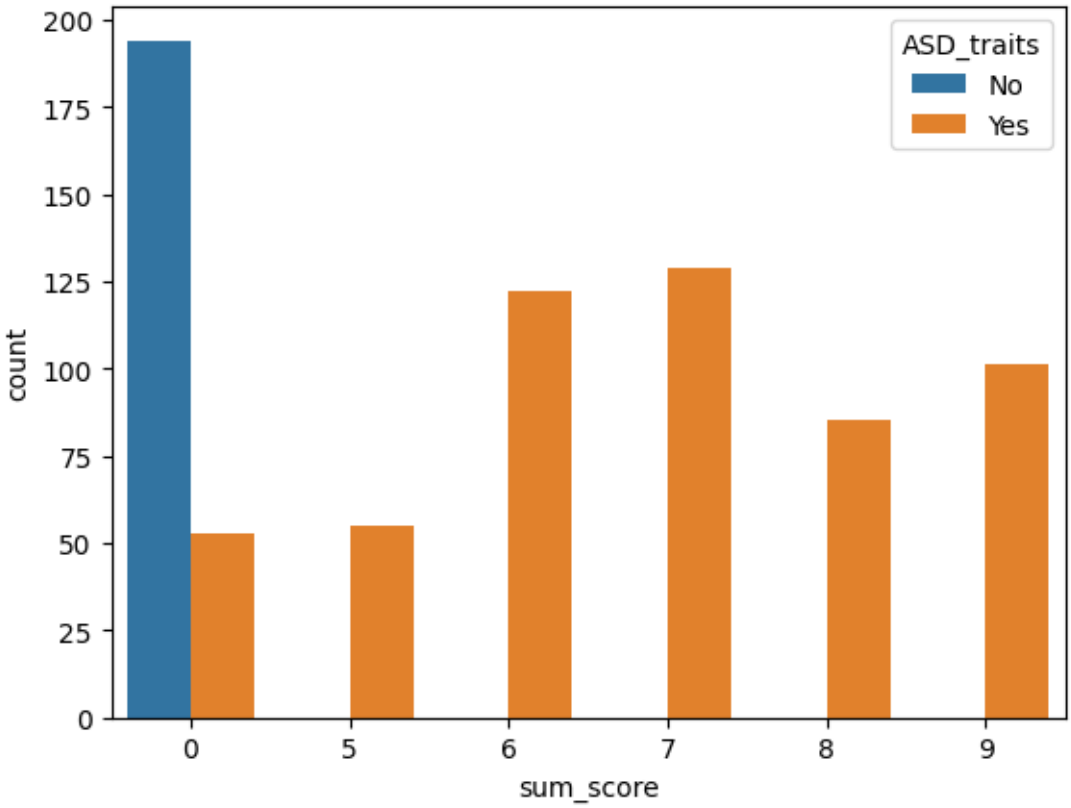
[47]:
```
def convertAge(age):
    if age < 4:
        return 'Toddler'
    elif age < 12:
        return 'Kid'
    elif age < 18:
        return 'Teenager'
    elif age < 40:
        return 'Young'
    else:
        return 'Senior'

df['ageGroup'] = df['Age_Years'].apply(convertAge)
```

[49]:
```
sb.countplot(x=df['ageGroup'], hue=df['ASD_traits'])
plt.show()
```



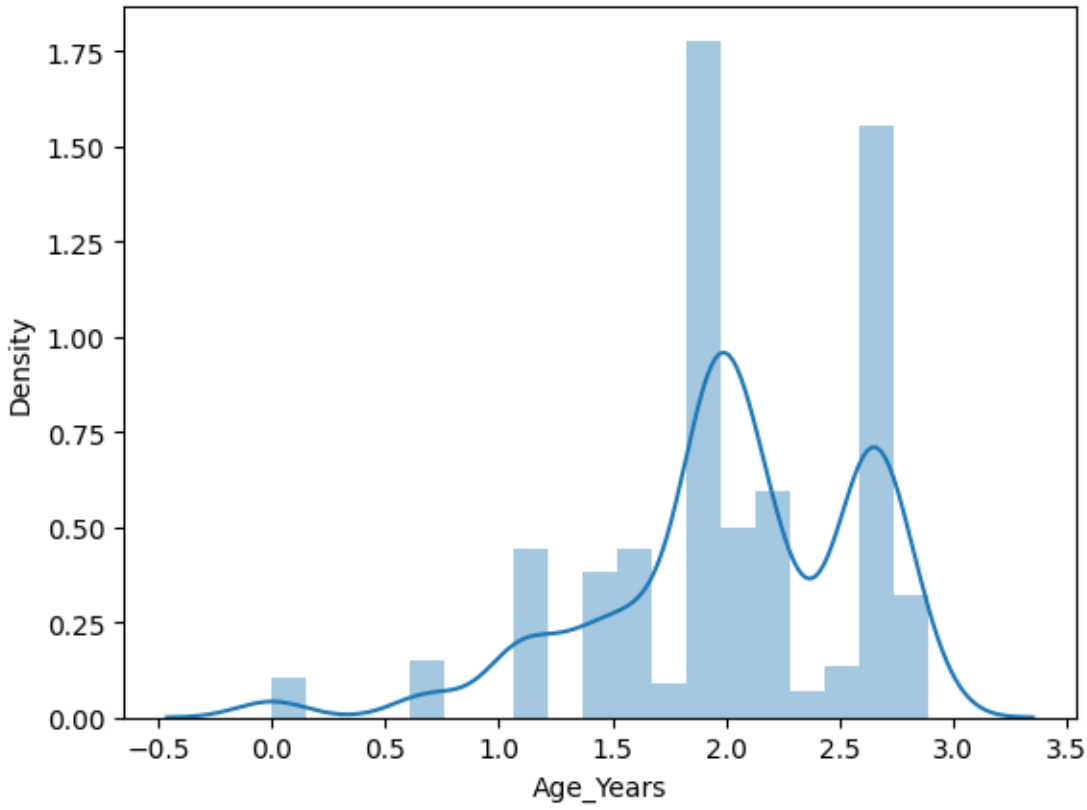
[51]:
```
def add_feature(data):
    score_columns = ['A1', 'A2', 'A3', 'A4', 'A5', 'A6', 'A7', 'A8', 'A9']

    data['sum_score'] = 0
    for col in score_columns:
        data['sum_score'] += data[col]

    data['ind'] = (
        data['Jaundice'].map({'yes': 1, 'no': 0}) +
        data['Family_mem_with_ASD'].map({'yes': 1, 'no': 0})
    )

    return data

df = add_feature(df)
```

[53]:
```
sb.countplot(x=df['sum_score'], hue=df['ASD_traits'])
plt.show()
```

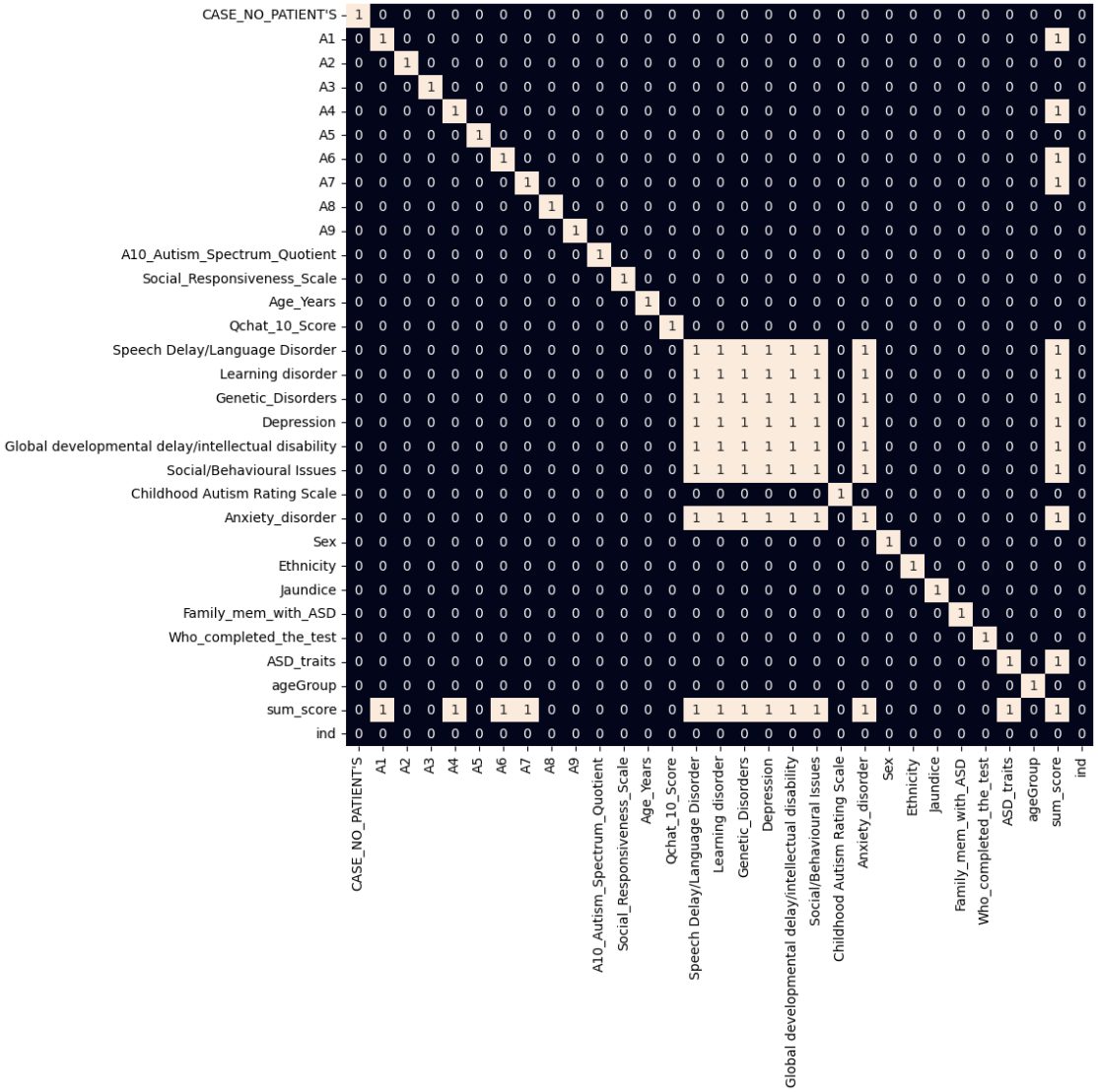


[55]:
```
df['Age_Years'] = df['Age_Years'].apply(lambda x: np.log(x))
```

[57]:
```
sb.distplot(df['Age_Years'])
plt.show()
```



[61]:
```
def encode_labels(data):
    for col in data.columns:
      if data[col].dtype == 'object':
        le = LabelEncoder()
        data[col] = le.fit_transform(data[col])

    return data

df = encode_labels(df)

plt.figure(figsize=(10,10))
sb.heatmap(df.corr() > 0.8, annot=True, cbar=False)
plt.show()
```



[65]:
```
removal = ["CASE_NO_PATIENT'S", 'ASD_traits']  # Remove ASD_traits from␣
↪features, use as target
features = df.drop(removal, axis=1)
target = df['ASD_traits']
```

[67]:
```
X_train, X_val, Y_train, Y_val = train_test_split(features, target, test_size =␣
↪0.2, random_state=10)
ros = RandomOverSampler(sampling_strategy='minority',random_state=0)
X, Y = ros.fit_resample(X_train,Y_train)
X.shape, Y.shape
```

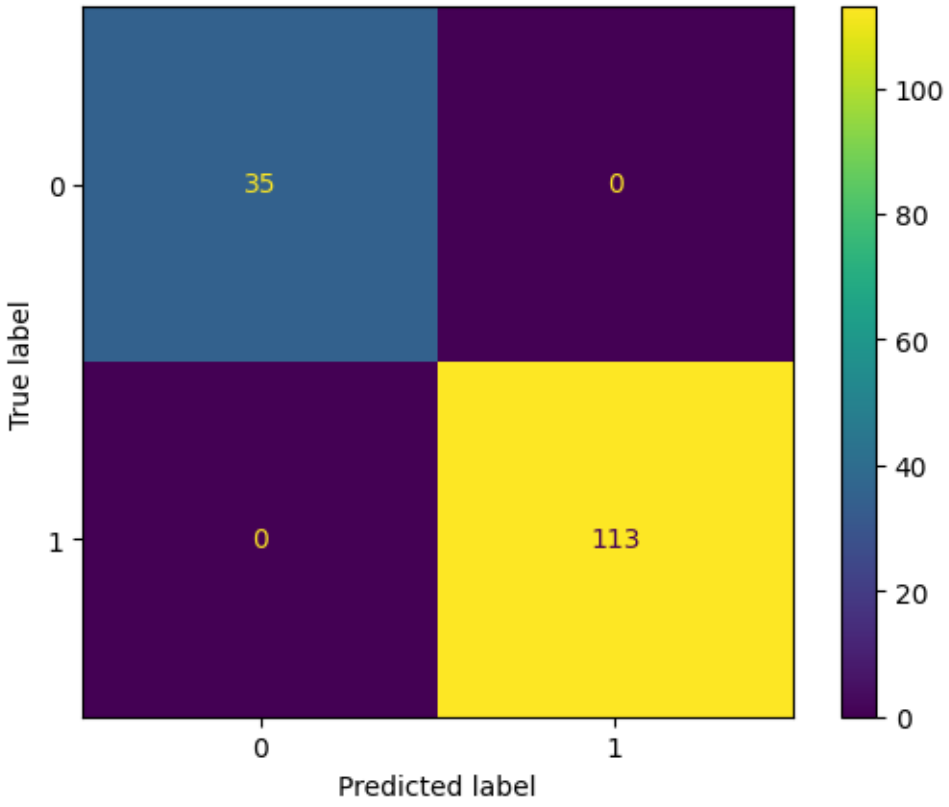
[67]: ((864, 29), (864,))

[69]:
```
scaler = StandardScaler()
X = scaler.fit_transform(X)
X_val = scaler.transform(X_val)
```

[75]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import RandomOverSampler
import pandas as pd
import numpy as np

X_train, X_val, Y_train, Y_val = train_test_split(features, target, test_size=0.
 ↪2, random_state=10)

ros = RandomOverSampler(sampling_strategy='minority', random_state=0)
X, Y = ros.fit_resample(X_train, Y_train)
X = X.fillna(0)
X_val = X_val.fillna(0)
models = [
    LogisticRegression(),
    SVC(kernel='rbf', probability=True),
    DecisionTreeClassifier()
]
for model in models:
    model.fit(X, Y)

    print(f'{model.__class__.__name__} :')
    print('Training ROC-AUC Score:', roc_auc_score(Y, model.predict_proba(X)[:,␣
 ↪1]))
    print('Validation ROC-AUC Score:', roc_auc_score(Y_val, model.
 ↪predict_proba(X_val)[:, 1]))
    print()
```

```
LogisticRegression :
Training ROC-AUC Score: 1.0
Validation ROC-AUC Score: 1.0

SVC :
Training ROC-AUC Score: 1.0
Validation ROC-AUC Score: 1.0

DecisionTreeClassifier :
Training ROC-AUC Score: 1.0
Validation ROC-AUC Score: 1.0
```

[77]:
```
from sklearn.metrics import ConfusionMatrixDisplay

ConfusionMatrixDisplay.from_estimator(models[0], X_val, Y_val)
plt.show()
```



[ ]:

Results & Discussion

All models (Logistic Regression, SVM, Decision Tree) achieved:

- Training ROC-AUC: 1.0
- Validation ROC-AUC: 1.0

This suggests highly separable classes after preprocessing and feature engineering. However, perfect scores could also suggest potential overfitting or ideal synthetic-like balance due to oversampling. The heatmap and correlation analysis also revealed useful insights—such as relationships between age, behavioral scores, and ASD prediction.

Conclusion

This project successfully demonstrates the application of machine learning models for ASD prediction. The excellent performance shows that the features used in the dataset are highly predictive. With careful preprocessing, even simple models can achieve strong results. This model, when further validated on real-world data, could be used as a support tool in early autism screening.

Future Scope

- Evaluate on real-time or clinical data
- Use more robust models like Random Forest or XGBoost
- Deploy the model into a user-friendly web or mobile interface
- Collaborate with pediatric or clinical research teams for validation

References

- scikit-learn Documentation
- imblearn Documentation
- Seaborn and Matplotlib Visualization Docs
- Articles on ASD screening using data science
- Source dataset used in DWDA mini project

Appendix

- Pie chart: ASD Traits distribution
- Heatmap: Feature correlation (above 0.8)
- Countplots: Behavioral & medical features vs ASD
- Confusion Matrix output
- ROC-AUC scores for all models
- Key Code Snippets: Data encoding, model training, evaluation