AUTISM PREDICTION FROM MEDICAL DATA

Introduction

About Autism

Autism is a neurodevelopmental disorder characterized by challenges in social interaction, communication difficulties, and restricted and repetitive patterns of behavior and interests. Autism affects individuals across their lifespan and can significantly impact their daily functioning, relationships, and overall quality of life.

Problem Statement

The problem addressed in this project is the need for accurate and timely autism prediction, particularly in the early stages of development. Early detection of autism spectrum disorder (ASD) is crucial for initiating appropriate interventions and support, but it can be challenging due to the diverse and subtle nature of ASD symptoms. This project aims to leverage machine learning techniques to develop a reliable and efficient system for autism prediction, with the goal of improving early identification and intervention for individuals with ASD.

Given a dataset composed of 1000 people who filled an app form, this project aims to use machine learning models to predict the likelihood of having autism.

About the Dataset

Dataset Size

1. train.csv 800 rows
2. test.csv 200 rows

Columns:

- ID - ID of the patient
- A1_Score to A10_Score - Score based on Autism Spectrum Quotient (AQ) 10 item screening tool
- age - Age of the patient in years
- gender - Gender of the patient
- ethnicity - Ethnicity of the patient
- jaundice - Whether the patient had jaundice at the time of birth
- autism - Whether an immediate family member has been diagnosed with autism
- contry_of_res - Country of residence of the patient
- used_app_before - Whether the patient has undergone a screening test before
- result - Score for AQ1-10 screening test
- age_desc - Age of the patient
- relation - Relation of patient who completed the test
- Class/ASD - Classified result as 0 or 1. Here 0 represents No and 1 represents Yes. This is the target column, and during submission submit the values as 0 or 1 only.

DATA PRE-PROCESSING

```
## Importing the necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
## Reading the data
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
```

```python
## Checking the head of the data
train.head()
```

```
   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]
```

```python
## Checking the column names in the dataframe
train.columns
```

```
Index(['ID', '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', 'age_desc', 'relation', 'Class/ASD'],
      dtype='object')
```

```python
## Finding the numerical and categorical columns
cat_cols = [feature for feature in train.columns if train[feature].dtypes == 'O']
num_cols = [feature for feature in train.columns if feature not in cat_cols]
```

```python
## Printing the numerical and categorical columns
print(f"Numerical columns: {num_cols}\n")
print(f"Categorical columns: {cat_cols}")
```

```
Numerical columns: ['ID', 'A1_Score', 'A2_Score', 'A3_Score', 'A4_Score', 'A5_Score',
'A6_Score', 'A7_Score', 'A8_Score', 'A9_Score', 'A10_Score', 'age', 'result',
'Class/ASD']

Categorical columns: ['gender', 'ethnicity', 'jaundice', 'austim', 'contry_of_res',
'used_app_before', 'age_desc', 'relation']
```

```python
## Finding the unique values in each of the categorical feature columns
for feature in cat_cols:
    print(f"{feature}:")
    print(f"Number of unique values in the {feature}: {train[feature].nunique()}")
    print(f"Unique values: {train[feature].unique()}")
    print('\n')
```

```
gender:
Number of unique values in the gender: 2
Unique values: ['f' 'm']


ethnicity:
Number of unique values in the ethnicity: 12
Unique values: ['?' 'White-European' 'Middle Eastern ' 'Pasifika' 'Black' 'Others'
 'Hispanic' 'Asian' 'Turkish' 'South Asian' 'Latino' 'others']


jaundice:
Number of unique values in the jaundice: 2
Unique values: ['no' 'yes']


austim:
Number of unique values in the austim: 2
Unique values: ['no' 'yes']


contry_of_res:
Number of unique values in the contry_of_res: 56
Unique values: ['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:
Number of unique values in the used_app_before: 2
Unique values: ['no' 'yes']


age_desc:
Number of unique values in the age_desc: 1
Unique values: ['18 and more']


relation:
Number of unique values in the relation: 6
Unique values: ['Self' 'Relative' 'Parent' '?' 'Others' 'Health care professional']
```

```
## Removing unnecessary columns
## Removing ID column since it doesn't provide any logical relation to the occurance
of the disease
## Removing the age_desc column since it has only one value. In other words, the
column has zero variance
train.drop(columns=['ID','age_desc'],axis=1,inplace=True)
```

```
## Checking the successful dropping of ID and age_desc columns
train.columns
```

```
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')
```

```
## Some of the columns have ? symbol instead of the record
## Here we will just add such records into the Others category
## Columns -- ethnicity, relation
train['ethnicity'] = np.where(train['ethnicity'] == '?', 'Others',train['ethnicity'])
train['relation'] = np.where(train['relation'] == '?', 'Others', train['relation'])
```

```
## Checking for successful replacement of records with ?
for feature in ['ethnicity','relation']:
    print(f"{feature}:")
    print(f"Number of unique values in the {feature}: {train[feature].nunique()}")
    print(f"Unique values: {train[feature].unique()}")
    print('\n')
```

```
ethnicity:
Number of unique values in the ethnicity: 11
Unique values: ['Others' 'White-European' 'Middle Eastern ' 'Pasifika' 'Black'
'Hispanic'
 'Asian' 'Turkish' 'South Asian' 'Latino' 'others']


relation:
Number of unique values in the relation: 5
Unique values: ['Self' 'Relative' 'Parent' 'Others' 'Health care professional']
```

```python
## In the feature column ethnicity, there are two types of other columns : 1. Others
2. others
## Let's just merge those records into one category named Others
train['ethnicity']= np.where(train['ethnicity'] == 'others', 'Others',
train['ethnicity'])

for feature in ['ethnicity']:
    print(f"{feature}:")
    print(f"Number of unique values in the {feature}: {train[feature].nunique()}")
    print(f"Unique values: {train[feature].unique()}")
    print('\n')
```

```
ethnicity:
Number of unique values in the ethnicity: 10
Unique values: ['Others' 'White-European' 'Middle Eastern ' 'Pasifika' 'Black'
'Hispanic'
 'Asian' 'Turkish' 'South Asian' 'Latino']
```

```python
## Removing unnecessary colummS

num_cols.remove('ID')
cat_cols.remove('age_desc')

for feature in cat_cols:
    print(f"{feature}:")
    print(f"Number of unique values in the {feature}: {train[feature].nunique()}")
    print(f"Unique values: {train[feature].unique()}")
    print('\n')
```

```
gender:
Number of unique values in the gender: 2
Unique values: ['f' 'm']


ethnicity:
Number of unique values in the ethnicity: 10
Unique values: ['Others' 'White-European' 'Middle Eastern ' 'Pasifika' 'Black'
'Hispanic'
 'Asian' 'Turkish' 'South Asian' 'Latino']


jaundice:
Number of unique values in the jaundice: 2
Unique values: ['no' 'yes']


austim:
Number of unique values in the austim: 2
Unique values: ['no' 'yes']
```

```
contry_of_res:
Number of unique values in the contry_of_res: 56
Unique values: ['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:
Number of unique values in the used_app_before: 2
Unique values: ['no' 'yes']


relation:
Number of unique values in the relation: 5
Unique values: ['Self' 'Relative' 'Parent' 'Others' 'Health care professional']
```

```
## Checking for missing values in the dataset
train.isnull().sum()
```

```
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                0
gender             0
ethnicity          0
jaundice           0
austim             0
contry_of_res      0
used_app_before    0
result             0
relation           0
Class/ASD          0
dtype: int64
```

It seems there are no missing values in the dataset

```python
## Checking whether the data is unbalanced or not
train['Class/ASD'].value_counts()
```

```
0    639
1    161
Name: Class/ASD, dtype: int64
```

```python
639/(161+639)
```

```
0.79875
```

This means that almost 80% of the target values are of single category.

The dataset seems to be unbalanced

```python
## Listing categorical columns
cat_cols
```

```
['gender',
 'ethnicity',
 'jaundice',
 'austim',
 'contry_of_res',
 'used_app_before',
 'relation']
```

```python
## Creating a copy of the original dataset before encoding (for visualization)
train_copy = train.copy()
```

```python
## Since we already have over 15 independent feature, we will use ordinal encoding instead of the one-hot encoding on the categorical features
from sklearn.preprocessing import OrdinalEncoder
oe = OrdinalEncoder(handle_unknown='use_encoded_value', unknown_value=60, dtype=np.int64)

train[cat_cols] = oe.fit_transform(train[cat_cols])

for feature in cat_cols:
    print(f"Unique values in {feature}:")
    print(f"{train[feature].unique()}\n")
```

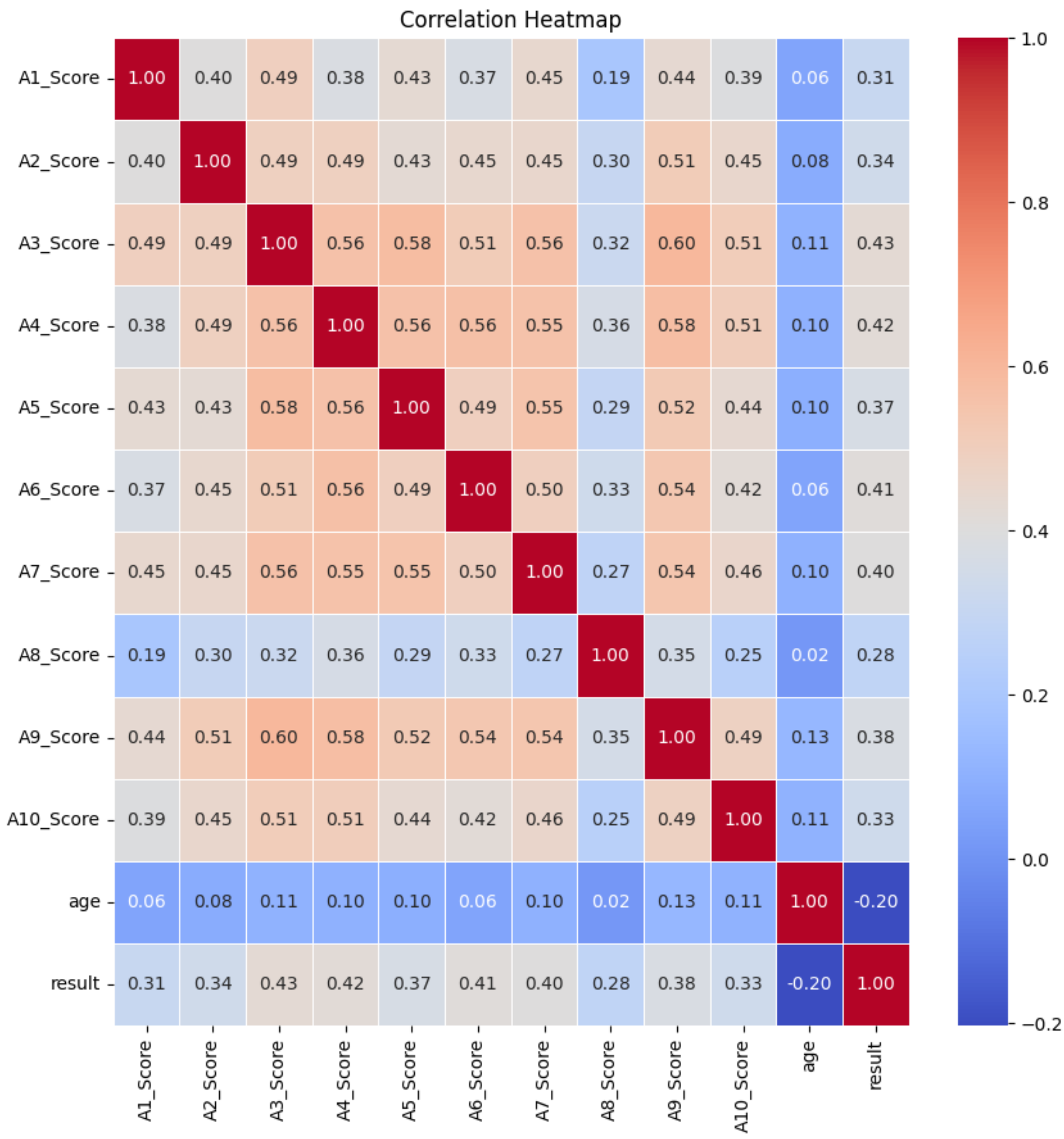
```
Unique values in gender:
[0 1]

Unique values in ethnicity:
[5 9 4 6 1 2 0 8 7 3]

Unique values in jaundice:
[0 1]

Unique values in austim:
[0 1]

Unique values in contry_of_res:
[ 7 25 54 46 31 53 13 36 15 32 52  6 51 27 21 33 55 19 35  0 39 29  1  9
 43 28  5 48 42 12  8  4 44 20 49 24 23  2 16 22 47 50 40 26  3 30 34 37
 45 18 38 41 17 11 14 10]

Unique values in used_app_before:
[0 1]

Unique values in relation:
[4 3 2 1 0]
```

```python
## Our training data is ready
train.head()
```

```
   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  \
0         0         1          1  38.172746       0          5         0
1         0         0          0  47.750517       1          5         0
2         1         1          1   7.380373       1          9         0
3         0         0          0  23.561927       0          5         0
4         0         0          0  43.205790       1          5         0

   austim  contry_of_res  used_app_before     result  relation  Class/ASD
0       0              7                0   6.351166         4          0
1       0             25                0   2.255185         4          0
2       1             54                0  14.851484         4          1
3       0             54                0   2.276617         4          0
4       0             46                0  -4.777286         4          0
```

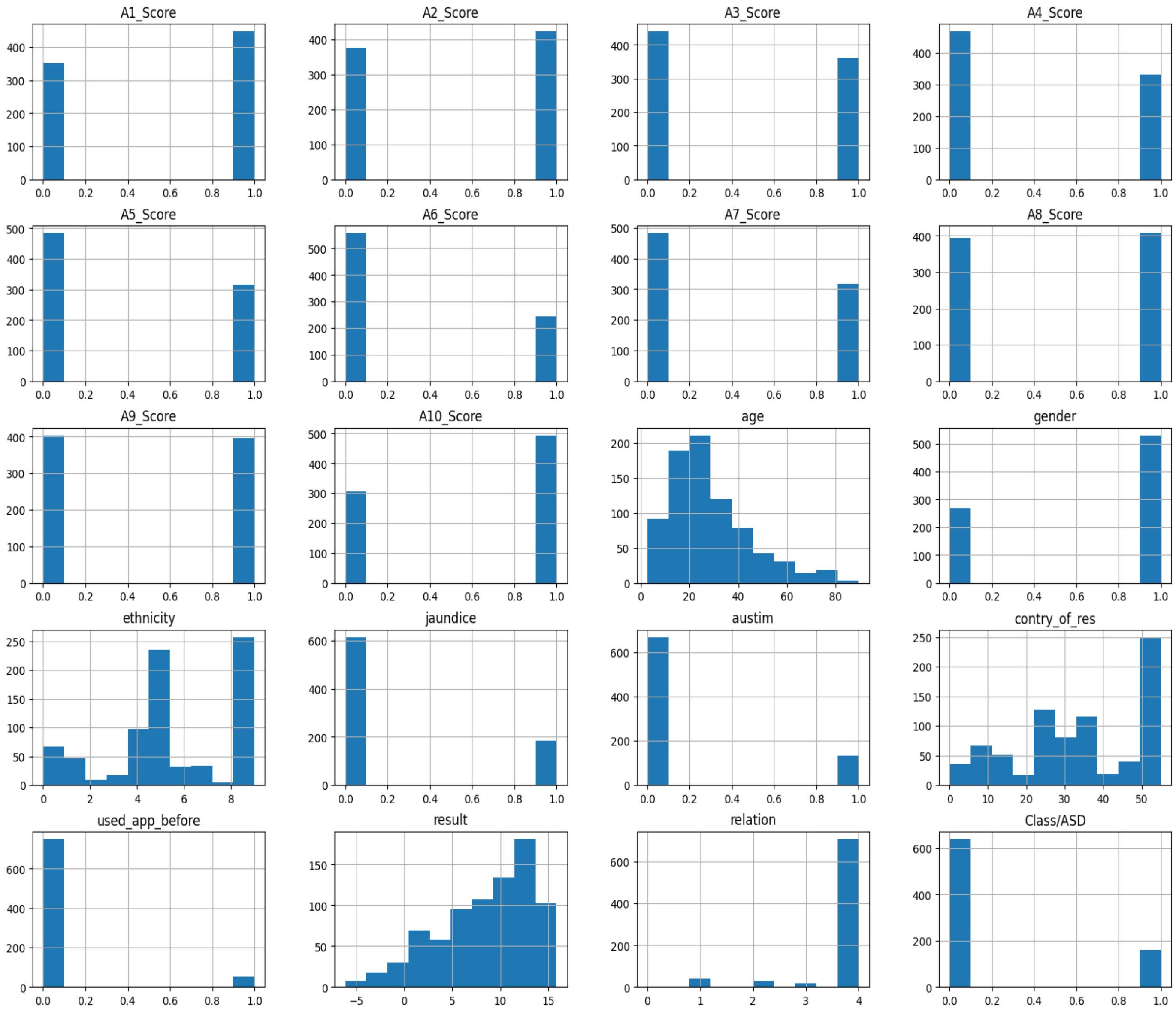
Data Visualization

```python
# Selecting numerical features for the heatmap
features_hm = ['A1_Score', 'A2_Score', 'A3_Score', 'A4_Score', 'A5_Score',
                       'A6_Score', 'A7_Score', 'A8_Score', 'A9_Score', 'A10_Score',
'age', 'result']

# Calculate the correlation matrix
correlation_matrix = train[features_hm].corr()

# Set up the matplotlib figure
plt.figure(figsize=(10, 10))

# Create a heatmap with the correlation matrix
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f",
linewidths=0.5)

plt.title('Correlation Heatmap')
plt.show()
```

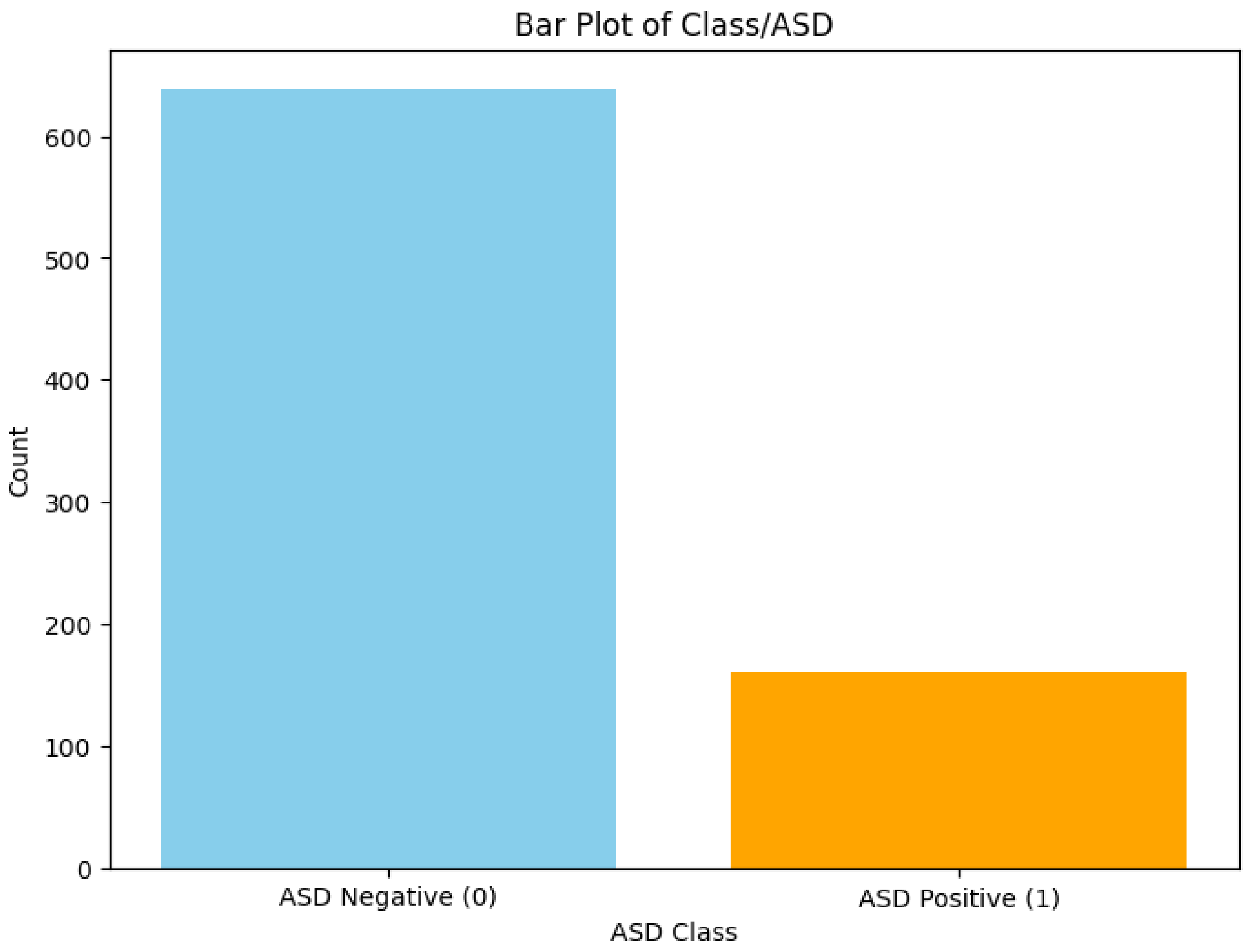


```
train.hist(figsize=(20,15))
```

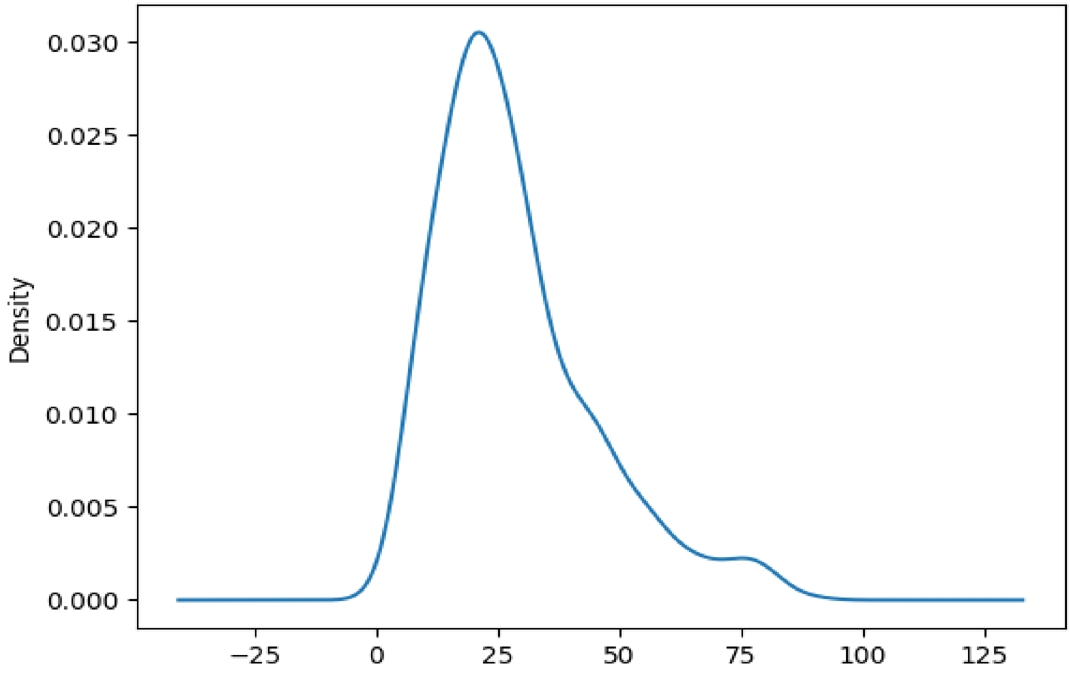
```
array([[<Axes: title={'center': 'A1_Score'}>,
        <Axes: title={'center': 'A2_Score'}>,
        <Axes: title={'center': 'A3_Score'}>,
        <Axes: title={'center': 'A4_Score'}>],
       [<Axes: title={'center': 'A5_Score'}>,
        <Axes: title={'center': 'A6_Score'}>,
        <Axes: title={'center': 'A7_Score'}>,
        <Axes: title={'center': 'A8_Score'}>],
       [<Axes: title={'center': 'A9_Score'}>,
        <Axes: title={'center': 'A10_Score'}>,
        <Axes: title={'center': 'age'}>,
        <Axes: title={'center': 'gender'}>],
       [<Axes: title={'center': 'ethnicity'}>,
        <Axes: title={'center': 'jaundice'}>,
        <Axes: title={'center': 'austim'}>,
        <Axes: title={'center': 'contry_of_res'}>],
       [<Axes: title={'center': 'used_app_before'}>,
        <Axes: title={'center': 'result'}>,
        <Axes: title={'center': 'relation'}>,
        <Axes: title={'center': 'Class/ASD'}>]], dtype=object)
```



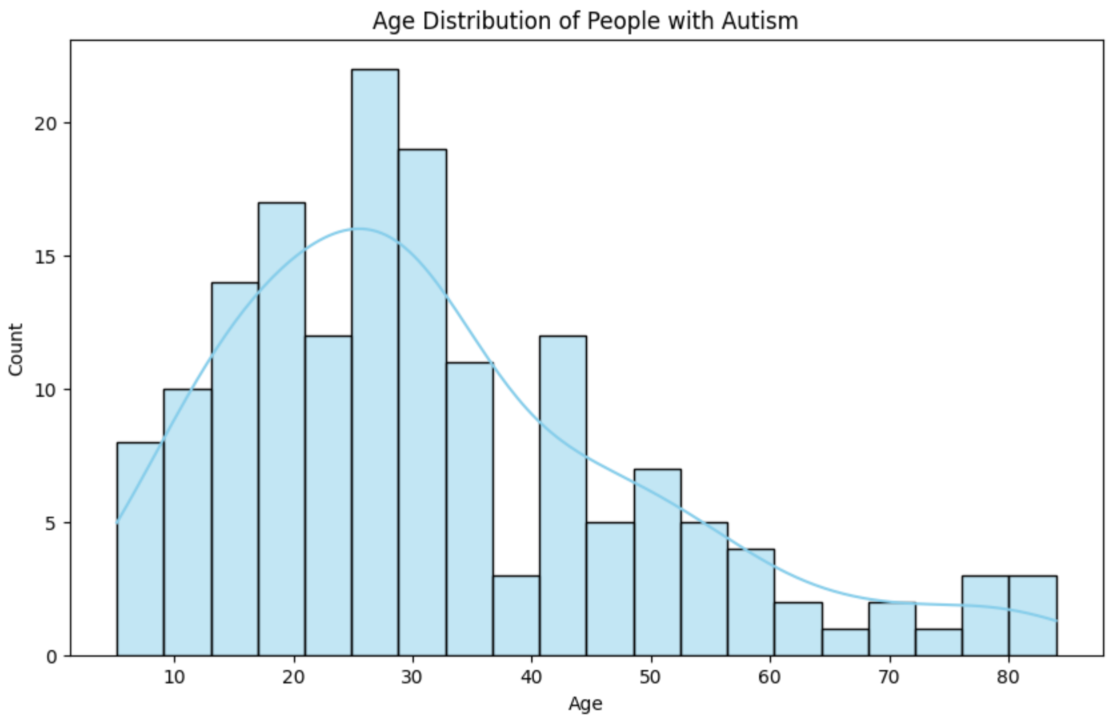
```python
# Plotting bar plot for Class/ASD to deduce the ratio of Autism-No Autism people in the training dataset
# Calculate the count of 0s and 1s


counts = train['Class/ASD'].value_counts()

plt.figure(figsize=(8, 6))
plt.bar(counts.index, counts.values, color=['skyblue', 'orange'])
plt.title('Bar Plot of Class/ASD')
plt.xlabel('ASD Class')
plt.ylabel('Count')
plt.xticks(counts.index, labels=['ASD Negative (0)', 'ASD Positive (1)'])
plt.show()
```



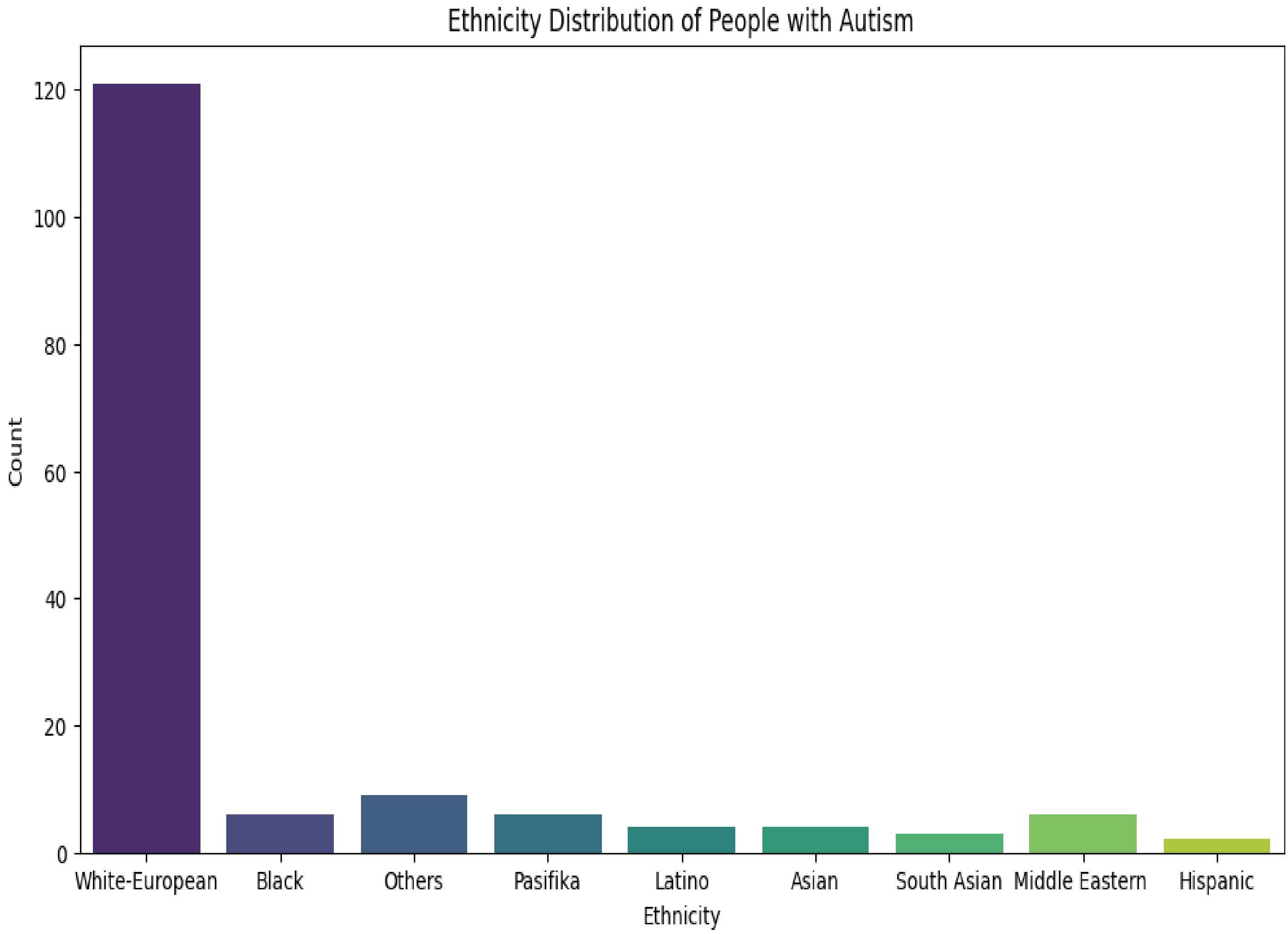
```
## Plotting the age group
train['age'].plot(kind='kde')
```



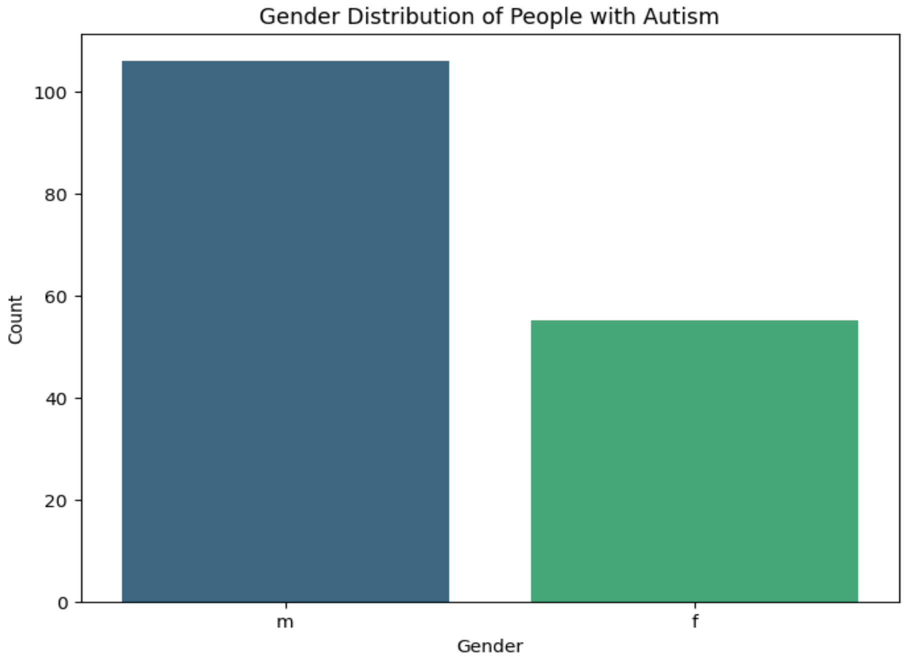

```
# Filter rows where Class/ASD is 1 (indicating people with autism)
asd_positive = train_copy[train_copy['Class/ASD'] == 1]

# Plotting age distribution for people with autism
plt.figure(figsize=(10, 6))
sns.histplot(asd_positive['age'], bins=20, kde=True, color='skyblue')
plt.title('Age Distribution of People with Autism')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



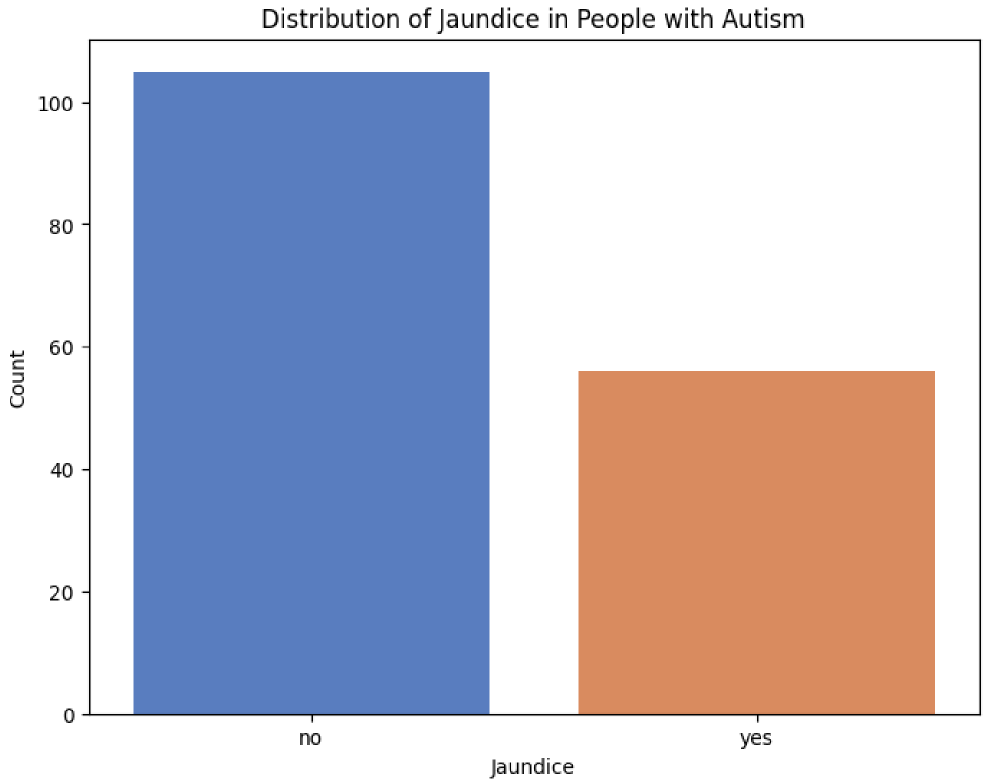
```python
# Plotting ethnicity distribution for people with autism

plt.figure(figsize=(12, 6))
sns.countplot(x='ethnicity', data=asd_positive, palette='viridis')
plt.title('Ethnicity Distribution of People with Autism')
plt.xlabel('Ethnicity')
plt.ylabel('Count')
plt.show()
```



```
# Plotting gender distribution for people with autism
plt.figure(figsize=(8, 6))
sns.countplot(x='gender', data=asd_positive, palette='viridis')
plt.title('Gender Distribution of People with Autism')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```




```
# Plotting jaundice distribution for people with autism
plt.figure(figsize=(8, 6))
sns.countplot(x='jaundice', data=asd_positive, palette='muted')
plt.title('Distribution of Jaundice in People with Autism')
plt.xlabel('Jaundice')
plt.ylabel('Count')
plt.show()
```



Model Training

```
## Splitting the train data into X_train and y_train
X_train = train.drop('Class/ASD', axis=1)
y_train = train['Class/ASD']
```

```
## Importing different model classes from the scikit-learn library
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,
GradientBoostingClassifier, StackingClassifier, VotingClassifier
```

```
## Importing a method for finding the cross validation score on the training data
from sklearn.model_selection import cross_val_score
```

```
## Creating a object for the models
lr = LogisticRegression(random_state=234, max_iter=3000)
svc = SVC(random_state=567,probability=True)
knc = KNeighborsClassifier()
rfc = RandomForestClassifier(max_depth=3, n_jobs=-1)
adab = AdaBoostClassifier(n_estimators=100, random_state=32389)
gradb = GradientBoostingClassifier(random_state=34990)
```

```
## Finding the cross validation score for every object that was created
model_lst = [lr, svc, knc, rfc, adab, gradb]

for model in model_lst:
    cvs = cross_val_score(model, X_train, y_train, cv=10, scoring = 'roc_auc',
n_jobs=-1).mean()
    print(f"Cross validation score for the {model}: {np.round(cvs,3)}\n")
```

```
Cross validation score for the LogisticRegression(max_iter=3000, random_state=234):
0.905

Cross validation score for the SVC(probability=True, random_state=567): 0.868

Cross validation score for the KNeighborsClassifier(): 0.811

Cross validation score for the RandomForestClassifier(max_depth=3, n_jobs=-1): 0.916

Cross validation score for the AdaBoostClassifier(n_estimators=100,
random_state=32389): 0.876

Cross validation score for the GradientBoostingClassifier(random_state=34990): 0.896
```

```python
## Trying out the voting classifier
from sklearn.metrics import roc_auc_score
import random

vc = VotingClassifier(estimators=
                     [('lr',lr), ('svc', svc), ('rfc', rfc), ('knc', knc)],
voting='soft')
vc.fit(X_train, y_train)
vc_scores = vc.predict_proba(X_train)[:,1]
vc_roc_auc_score = np.round(roc_auc_score(y_train, vc_scores),3)
print(f"Cross validation score for the voting classifier: {vc_roc_auc_score}")
```

```
Cross validation score for the voting classifier: 0.938
```

```python
## Trying out another voting classifier
vc2 = VotingClassifier(estimators=
                     [('lr',lr),('rfc', rfc), ('adab',adab), ('gradb', gradb)],
voting='soft')
vc2.fit(X_train, y_train)
vc2_scores = vc2.predict_proba(X_train)[:,1]
vc2_roc_auc_score = np.round(roc_auc_score(y_train, vc2_scores),3)
print(f"Cross validation score for the voting classifier: {vc2_roc_auc_score}")
```

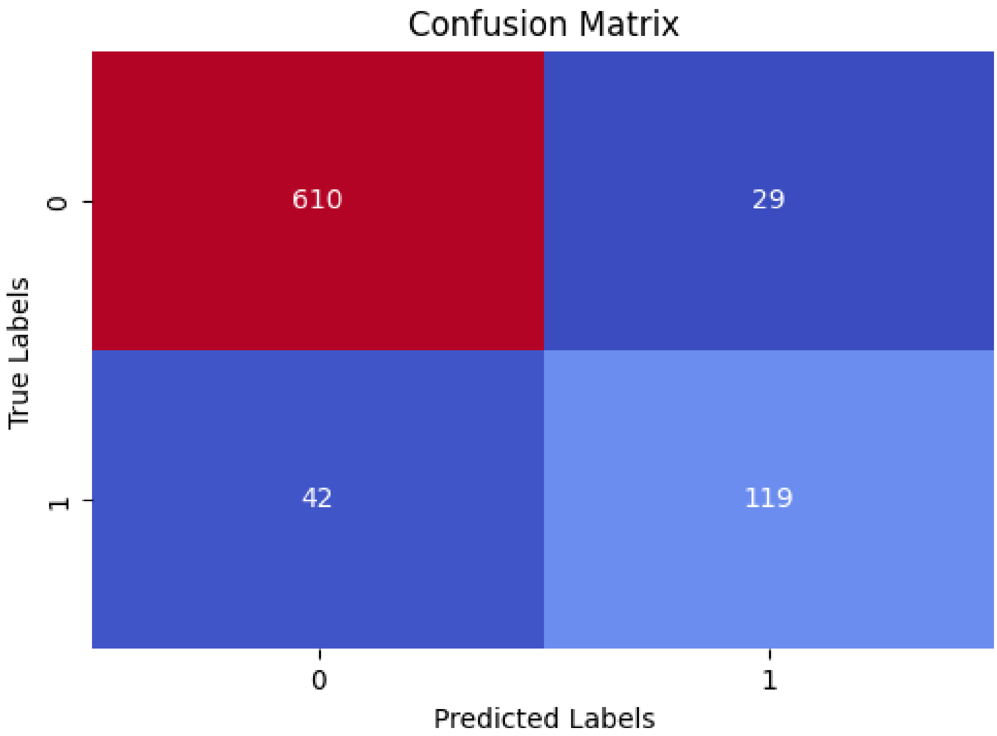
```
Cross validation score for the voting classifier: 0.965
```

```python
## Trying out the stacking classifier
estimators = [('vc',vc), ('vc2', vc2)]

sc = StackingClassifier(estimators=estimators, final_estimator=rfc)
sc.fit(X_train, y_train)
sc_score = sc.predict_proba(X_train)[:,1]
sc_roc_auc_score = np.round(roc_auc_score(y_train, sc_score), 3)
print(f"Cross validation score for the stacking classifier: {sc_roc_auc_score}")
```

```
Cross validation score for the stacking classifier: 0.952
```

Voting classifier number 2 seems to be the best model out of all the ones that we trained on the training data

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

# Obtain the predicted labels for the train set
predicted = vc2.predict(X_train)

# Create a confusion matrix
cm = confusion_matrix(y_train, predicted)

# Plot the confusion matrix
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, cmap="coolwarm", fmt="d", cbar=False)
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
plt.title("Confusion Matrix")
plt.show()
```




```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# Calculate accuracy
accuracy = accuracy_score(y_train, predicted)

# Calculate precision
precision = precision_score(y_train, predicted)

# Calculate recall
recall = recall_score(y_train, predicted)

# Calculate F1 score
f1 = f1_score(y_train, predicted)

print(f"Accuracy: {accuracy:.3f}")
print(f"Precision: {precision:.3f}")
print(f"Recall: {recall:.3f}")
print(f"F1 Score: {f1:.3f}")
```

```
Accuracy: 0.911
Precision: 0.804
Recall: 0.739
F1 Score: 0.770
```

PREPROCESSING THE TEST DATA

```
test.head()
```

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

   A8_Score  A9_Score  ...        age  gender       ethnicity jaundice austim  \
0         0         1  ...  15.599481       m  White-European      yes     no   
1         1         0  ...  27.181099       m           Asian       no     no   
2         1         1  ...  31.643906       m  White-European      yes     no   
3         0         0  ...  25.369210       m               ?       no     no   
4         0         0  ...   9.078580       m               ?       no     no   

  contry_of_res used_app_before     result     age_desc relation  
0         India              no  12.399055  18 and more     Self  
1        Mexico              no   6.551598  18 and more     Self  
2         Egypt              no   3.180663  18 and more     Self  
3         India              no   2.220766  18 and more     Self  
4         Italy              no   7.252028  18 and more     Self  

[5 rows x 21 columns]
```

```
## Finding the numerical and categorical columns
cat_cols_test = [feature for feature in test.columns if test[feature].dtypes == 'O']
num_cols_test = [feature for feature in test.columns if feature not in cat_cols_test]

print(f"Numerical columns: {num_cols_test}\n")
print(f"Categorical columns: {cat_cols_test}")
```

```
Numerical columns: ['ID', 'A1_Score', 'A2_Score', 'A3_Score', 'A4_Score', 'A5_Score', 'A6_Score', 'A7_Score', 'A8_Score', 'A9_Score', 'A10_Score', 'age', 'result']
```

```
Categorical columns: ['gender', 'ethnicity', 'jaundice', 'austim', 'contry_of_res', 'used_app_before', 'age_desc', 'relation']
```

```python
## Finding the unique values in each of the categorical feature columns
for feature in cat_cols_test:
    print(f"{feature}:")
    print(f"Number of unique values in the {feature}: {test[feature].nunique()}")
    print(f"Unique values: {test[feature].unique()}")
    print('\n')
```

```
gender:
Number of unique values in the gender: 2
Unique values: ['m' 'f']


ethnicity:
Number of unique values in the ethnicity: 11
Unique values: ['White-European' 'Asian' '?' 'Middle Eastern ' 'South Asian'
'Pasifika'
 'Turkish' 'Latino' 'Black' 'Others' 'Hispanic']


jaundice:
Number of unique values in the jaundice: 2
Unique values: ['yes' 'no']


austim:
Number of unique values in the austim: 2
Unique values: ['no' 'yes']


contry_of_res:
Number of unique values in the contry_of_res: 35
Unique values: ['India' 'Mexico' 'Egypt' 'Italy' 'Australia' 'United States' 'Jordan'
 'Burundi' 'United Kingdom' 'Canada' 'Germany' 'Russia' 'Spain' 'Austria'
 'Iran' 'New Zealand' 'Bolivia' 'United Arab Emirates' 'Uruguay' 'Lebanon'
 'France' 'Netherlands' 'Bahamas' 'Iceland' 'Sri Lanka' 'Afghanistan'
 'Pakistan' 'Malaysia' 'Aruba' 'Ireland' 'Viet Nam' 'Tonga' 'Philippines'
 'Azerbaijan' 'Czech Republic']


used_app_before:
Number of unique values in the used_app_before: 2
Unique values: ['no' 'yes']


age_desc:
Number of unique values in the age_desc: 1
Unique values: ['18 and more']


relation:
Number of unique values in the relation: 6
Unique values: ['Self' 'Parent' '?' 'Relative' 'Others' 'Health care professional']
```

```python
## Some of the columns present in the dataset have a ? instead of a record
## Columns -- ethnicity and relation
test['ethnicity'] = np.where(test['ethnicity'] == '?', 'Others', test['ethnicity'])
test['relation'] = np.where(test['relation'] == '?', 'Others', test['relation'])

for feature in cat_cols_test:
    print(f"{feature}:")
    print(f"Number of unique values in the {feature}: {test[feature].nunique()}")
    print(f"Unique values: {test[feature].unique()}")
    print('\n')
```

```
gender:
Number of unique values in the gender: 2
Unique values: ['m' 'f']


ethnicity:
Number of unique values in the ethnicity: 10
Unique values: ['White-European' 'Asian' 'Others' 'Middle Eastern ' 'South Asian'
 'Pasifika' 'Turkish' 'Latino' 'Black' 'Hispanic']


jaundice:
Number of unique values in the jaundice: 2
Unique values: ['yes' 'no']


austim:
Number of unique values in the austim: 2
Unique values: ['no' 'yes']


contry_of_res:
Number of unique values in the contry_of_res: 35
Unique values: ['India' 'Mexico' 'Egypt' 'Italy' 'Australia' 'United States' 'Jordan'
 'Burundi' 'United Kingdom' 'Canada' 'Germany' 'Russia' 'Spain' 'Austria'
 'Iran' 'New Zealand' 'Bolivia' 'United Arab Emirates' 'Uruguay' 'Lebanon'
 'France' 'Netherlands' 'Bahamas' 'Iceland' 'Sri Lanka' 'Afghanistan'
 'Pakistan' 'Malaysia' 'Aruba' 'Ireland' 'Viet Nam' 'Tonga' 'Philippines'
 'Azerbaijan' 'Czech Republic']


used_app_before:
Number of unique values in the used_app_before: 2
Unique values: ['no' 'yes']


age_desc:
Number of unique values in the age_desc: 1
Unique values: ['18 and more']


relation:
Number of unique values in the relation: 5
Unique values: ['Self' 'Parent' 'Others' 'Relative' 'Health care professional']
```

```
## Checking for the missing values in the dataset
test.isnull().sum()
```

```
ID                 0
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                0
gender             0
ethnicity          0
jaundice           0
austim             0
contry_of_res      0
used_app_before    0
result             0
age_desc           0
relation           0
dtype: int64
```

No missing values in the test data also

```
## Removing useless columns from the dataset
## Removing ID column since it doesn't contribute to the prediction of the autism as we can tell by our logic
## Removing the age_desc columns since the column has only one value. In other words, the column has zero variance
test.drop(['ID','age_desc'],axis=1,inplace=True)
```

```
test.columns
```

```
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'],
      dtype='object')
```

```
num_cols_test.remove('ID')
```

```
cat_cols_test.remove('age_desc')
```

```
print(f"Numerical columns: {num_cols_test}\n")
print(f"Categorical columns: {cat_cols_test}")
```

```
Numerical columns: ['A1_Score', 'A2_Score', 'A3_Score', 'A4_Score', 'A5_Score', 'A6_Score', 'A7_Score', 'A8_Score', 'A9_Score', 'A10_Score', 'age', 'result']

Categorical columns: ['gender', 'ethnicity', 'jaundice', 'austim', 'contry_of_res', 'used_app_before', 'relation']
```

```python
## Encoding the categorical columns
test[cat_cols_test] = oe.transform(test[cat_cols_test])

for feature in cat_cols_test:
    print(f"{feature}:")
    print(f"Number of unique values in the {feature}: {test[feature].nunique()}")
    print(f"Unique values: {test[feature].unique()}")
    print('\n')
```

```
gender:
Number of unique values in the gender: 2
Unique values: [1 0]


ethnicity:
Number of unique values in the ethnicity: 10
Unique values: [9 0 5 4 7 6 8 3 1 2]


jaundice:
Number of unique values in the jaundice: 2
Unique values: [1 0]


austim:
Number of unique values in the austim: 2
Unique values: [0 1]


contry_of_res:
Number of unique values in the contry_of_res: 33
Unique values: [25 34 19 29  6 54 31 14 53 15 22 42 47  7 26 36 12 52 60 21 35  9 24
48
  0 40 33  5 28 55 50  8 18]


used_app_before:
Number of unique values in the used_app_before: 2
Unique values: [0 1]


relation:
Number of unique values in the relation: 5
Unique values: [4 2 1 3 0]
```

```python
test.columns
```

```
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'],
      dtype='object')
```

test.head

```
<bound method NDFrame.head of      A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  
A6_Score  A7_Score  \
0           1         1         0         0         1         1         0   
1           1         0         0         0         0         0         0   
2           1         1         1         0         1         1         0   
3           0         0         0         0         0         0         0   
4           0         0         0         1         0         0         0   
..        ...       ...       ...       ...       ...       ...       ...   
195         1         1         0         0         1         0         0   
196         1         0         0         0         0         0         0   
197         1         0         0         0         0         0         1   
198         0         1         0         0         0         0         0   
199         1         0         0         0         0         0         1   

     A8_Score  A9_Score  A10_Score        age  gender  ethnicity  jaundice  \
0           0         1          1  15.599481       1          9         1   
1           1         0          0  27.181099       1          0         0   
2           1         1          1  31.643906       1          9         1   
3           0         0          0  25.369210       1          5         0   
4           0         0          0   9.078580       1          5         0   
..        ...       ...        ...        ...     ...        ...       ...   
195         1         1          1  23.099434       1          1         0   
196         0         0          1  13.935726       1          5         0   
197         0         1          1  22.760041       1          5         0   
198         1         0          1  24.352584       0          5         0   
199         1         0          1  45.713232       0          5         0   

     austim  contry_of_res  used_app_before     result  relation  
0         0             25                0  12.399055         4  
1         0             34                0   6.551598         4  
2         0             19                0   3.180663         4  
3         0             25                0   2.220766         4  
4         0             29                0   7.252028         4  
..      ...            ...              ...        ...       ...  
195       0              8                0  -1.915659         4  
196       0             25                0   0.520234         4  
197       0             36                0   3.498948         1  
198       0             54                0   5.594550         4  
199       0             18                0   9.532981         4  

[200 rows x 19 columns]>
```

Making predictions for the test data using the trained voting classifier number 2

```
final_predictions = vc2.predict(test)
```

```
final_predictions
```

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
       1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0])
```

```
len(final_predictions)
```

```
200
```