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Analyzing Autism Spectrum Disorder in Children

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***Abstract*—Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that presents diagnostic challenges. This study examines a dataset that includes demographic, medical, and familial variables, in addition to responses to the 10-item Autism Spectrum Questionnaire for Children aged 4-11 years old (AQ-10-Child) to assess their potential in improving ASD detection. Both responses from parents of these children and self-reporting are integrated. The dataset is available at UCI Machine Learning Repository. Analyzing 292 participants, this research found no significant correlations between family history of ASD, jaundice, gender, and ethnicity, and ASD, likely due to the small sample size. These findings highlight the need for larger, more diverse datasets to improve diagnostic accuracy of ASD. Future research should focus on integrating machine learning and AI-driven tools to enhance early ASD detection and intervention strategies.**

Keywords—Autism Spectrum Disorder, diagnostic tools, dataset analysis, early diagnosis

I. Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by challenges in communication, behavior, and learning. While symptoms can emerge at any age, they are most often identified in early childhood. The severity of ASD varies widely, from mild communication and behavioral challenges to more severe cases where individuals may be non-verbal and face significant difficulties with social interaction. This variability, combined with limited diagnostic tools and datasets, makes diagnosing ASD a complex and often subjective process.

To address these challenges, this study evaluates the accuracy and effectiveness of a newly created dataset designed to enhance the diagnostic process for ASD. The dataset includes an expanded range of variables such as demographic factors (gender, ethnicity, country of residence), medical history (e.g., jaundice), and familial factors (e.g., family history of ASD). This study aims to determine whether the inclusion of these variables can improve the diagnostic process by identifying the most significant predictors of ASD in children.

To guide the analysis, the question, “Which factors (age, gender, ethnicity, country of residence, jaundice, etc.) are the most significant predictors for ASD in children?” is proposed. Answering this question will provide a more comprehensive and accurate approach to diagnosis.

This study involves data [1] from 292 participants, incorporating both demographic and behavioral information. Ten behavioral features from the AQ-10-Child questionnaire and ten individual characteristics associated with autism detection in controlled groups were recorded. Using this comprehensive dataset, the study analyzes these variables to evaluate their predictive power and the overall accuracy of the diagnostic process.

This paper is organized as follows: section II presents the related work. In section III, the description of the dataset is provided. In Section IV, experimental results and analysis are included. Finally, section V offers the conclusion and future work.

II. Related Work

Cheng *et al.* focused on the diagnostic process for Autism Spectrum Disorder (ASD) [2]. Because of the focus on questionnaires, observation, and video analysis, there is a high reliance on professionals with massive labor costs. The solution that is offered from the study is a standardized platform for gathering and analyzing behavioral data within an application to aid the ASD diagnosis process. By having a structured process for assessing, the system can automatically evaluate the children and diagnose them with an accuracy of 88.42% for an average age of 24 months. This performance is comparable to human experts in the field and has great potential to be used in underdeveloped areas that are lacking medical resources.

Horlin *et al.* analyzed the impact of delayed diagnosis of Autism Spectrum Disorders (ASD) on costs for individuals, families, and the community [3]. The study utilized a registry-based questionnaire survey targeting all families with a child diagnosed with ASD in Western Australia. They found that nearly 90 % of the family expenses were due to loss of income from reduced employment opportunities for caregivers. Furthermore, they found that each additional ASD symptom increased the annual cost. Although there was little direct impact of diagnostic delay on costs, a slight increase in ASD symptoms was associated with delays, indirectly influencing the overall expenses. They suggested that early diagnosis and intervention could reduce symptoms, potentially mitigating these financial burdens.

Scassellati investigated social robots that can recognize and respond to social cues [4]. These robots can be applied to help with the diagnosis process of Autism Spectrum Disorder (ASD) through pattern recognition. The author stated that the main issue with the diagnosis process is that there is no blood test or other physical tests that can diagnose a patient. It is only possible with an examination with a clinician who can observe the patterns of the individual to see if it could fall under the diagnosis. The study found that social robots can track different aspects of patients while they are being engaged. This cannot be done without the assistance of technology because it is impossible to track all these metrics without many sensors. It was found that by using these social robots, allow clinicians to gain a unique perspective to address the problems with diagnosing autism.

Schopler *et al*. discovered the Childhood Autism Rating Scale (CARS), which is a diagnostic tool for identifying autism in children [5]. CARS evaluates a child's behavior through direct observation and caregiver reports. It measures across fifteen domains, including social interactions, communication, emotional response, listening response, and body use, and that provide a score that helps classify the stage of autism. CARS was developed to offer a more objective and quantifiable way of diagnosing autism. CARS's reliability and validity have been supported by numerous studies, and it has been updated over time to refine its application in diagnosing autism spectrum disorders (ASD).

Han *et al.* proposed a multimodal system for diagnosing Autism Spectrum Disorder (ASD) in children [6]. The system integrates various methods including behavior tracking, physiological signals, and machine learning techniques to improve diagnostic accuracy. The system was tested with multiple datasets, and the results demonstrated an enhanced identification accuracy compared to traditional diagnostic methods. This approach offers great potential in early detection of ASD, particularly in clinical settings that require comprehensive assessments from multiple data sources.

Noris *et el.* Discovered that Autism Spectrum Disorder (ASD) touches 1 in every 160 children [7]. There are many atypical visual behaviors that have been noticed in children with autism such as looking at the mouth rather than the eyes when looking at the face and difficulties with paying attention. Earlier studies observed that children with ASD would look with the corner of their eyes when they are looking at other people. One common symptom related to ASD is the downcast gaze. To address the evaluation of the naturalistic interactions, they have developed WearCam, which is a head-mounted eye-tracker that is designed to record the view filed as seen by the child. In this study, they presented 24 children (12 with ASD and 12 without). As a result, the children with ASD presented a gaze pattern which was the lower part of the vertical field of view and kept their gaze lower than the typical developed children which means that they discovered the lateral field of view more. That means that the children with ASD would look at things that would not perturb them.

McCarty *et el.* examined the ongoing challenges of early diagnosis of ASD [8]. They pointed out that ASD diagnosis is based on identifying abnormal behaviors, and diagnostic tools may be biased due to unpredictable factors in the interaction between the examiner and the child. Furthermore, they noted that these behaviors often do not emerge until the child reaches a certain age and the disorder is well established. They also raised concerns about universal screening for all toddlers, citing the low implementation rate and the strain it places on the healthcare system. Moreover, they criticized the accuracy of screening tests, noting that, due to a prevalence rate of 2%, only 33% of children identified by the "Modified Checklist for Autism in Toddlers (with Follow-Up)" were diagnosed with ASD. They proposed a multistep screening system to more accurately identify children at higher risk for ASD.

Yates *et el.* systematically summarized an assessment framework for specialists diagnosing ASD [9]. They described ASD as a neurodevelopmental disorder, identifying symptoms such as difficulties in social communication, repetitive behaviors, regression, learning disabilities, epilepsy, and disturbances in behavior, attention, and emotion. They suggested that in high-functioning ASD, the risk for additional difficulties is increased. Then, they highlighted the challenges in evaluating children with possible ASD, noting the difficulty in distinguishing whether symptoms are caused by ASD itself, comorbid conditions, environmental factors, or a combination of these. They emphasized the importance of multiagency assessment for an accurate diagnosis.

Booth *et al.* evaluated the effectiveness of the Autism Spectrum Quotient (AQ-10) as a brief screening tool for the rapid diagnosis of ASD [10]. The study compared the AQ-10 scores with those of the full version, AQ-50, by dividing participants into samples of individuals diagnosed with ASD and those without a diagnosis. The AQ-10 was developed as a shortened version of the AQ-50, selecting two of the most discriminative items from each of the five subscales (social interaction, communication, attention to detail, attention switching, and imagination). Using Receiver Operating Characteristic (ROC) analysis, the AQ-10 demonstrated an AUC (Area Under Curve) of 90.3%, with a sensitivity of 79.9% and a specificity of 87.3% at a cut-off score of 6. The authors indicated that the AQ-10 showed little reduction in discriminative power compared to the AQ-50, confirming its utility as an effective brief screening tool for adults.

Wakabayashi *et al.* conducted a study in Japan using the AQ-50 for children to evaluate if the reliability and validity observed in the UK could be generalized across cultures [11]. The study compared AQ scores between clinical groups diagnosed with Asperger syndrome/high-functioning autism (AS/HFA) and control groups. They found higher AQ-scores for males in the control group but no differences in the clinical group. The Japanese AQ-scores were slightly lower than those in the UK, which they hypothesized could be due to cultural differences in introversion. Despite this, they showed the score differences between clinical and control groups were consistent across both cultures, supporting the AQ's cross-cultural reliability.

Chandra *et al.* focused on using machine learning techniques to detect Autism Spectrum Disorder (ASD) based on visual data [12]. Autism Spectrum Disorder (ASD) is

known as complex neuro-developmental conditions, which have an impact on behavior, social interactions, and communication. The early noticing and intervention for people who have ASD by increasing social and communication skills, and independent abilities, can grow and improve the outcomes. As people with ASD may have different facial expressions from people with typical development, deep learning algorithms can help in early facial image noticing of ASD. They used two pre-trained models VGG16 and VGG19, to analyze a dataset split into training, testing, and validation sets. The best accuracy was 82.5% for VGG-19 and 80% for VGG-16. The authors concluded that convolutional neural network (CNN) is the most effective machine learning algorithm for identifying patients with ASD.

Wang *et al.* conducted a comprehensive survey on current diagnostic techniques and intervention strategies for Autism Spectrum Disorder (ASD) in children [13]. The article explored various methods, from behavioral to neurological approaches, highlighting gaps in early diagnosis and personalized intervention plans. They also discussed the importance of integrating AI-driven systems to enhance the effectiveness of ASD treatments. The authors emphasized that future research should focus on creating tailored interventions and diagnostic models that adapt to the individual needs of children with ASD.

Linstead *et al.* applied neural networks to predict learning outcomes in children with Autism Spectrum Disorder (ASD) undergoing Applied Behavior Analysis (ABA) therapy [14]. The study found a strong link between high-intensity ABA treatment, which focuses on skills like language and social interaction, and better outcomes such as higher IQ scores and success in general education. The research also highlighted key factors like treatment intensity, supervision, age, and gender in optimizing learning. Neural networks were found to be valuable in predicting mastery of specific learning objectives and enhancing personalized therapy.

Rajagopalan *et al.* investigated methods for detecting self-stimulatory behaviors (stimming) to aid in the diagnosis of Autism Spectrum Disorder (ASD) [15]. Their research focused on using video processing techniques to automatically track and analyze these repetitive behaviors, which are a common symptom of ASD. The proposed system successfully identified stimming behaviors in various environments, offering a non-invasive and reliable tool for early diagnosis. The findings of this study suggested that automated behavior tracking could become a key element in clinical diagnostic processes, reducing reliance on subjective observation.

Ackovska *et al.* discussed that over the past fifteen years, there has been a lot of progress in treating autistic children through robotic interaction for therapeutic purposes [16]. There is a wide range of symptoms that specify many people who have ASD. People with ASD sense, hear, and see everything around them differently from typically developed people, and they may have difficulties with learning and communicating with people. Robot assisted therapy (RAT) can be used in many ways such as social or teaching aspects. In therapy, humanoid robots have been used as they are safe, friendly, and have great benefits while playing and teaching autistic children. In the study, they had an 83% rate of success, which means that robotic therapy has good outcomes and cannot be ignored because the target group can have some challenges.

III. DATASET DESCRIPTION

The dataset by Thabtah [1] represents responses to the 10-item Autism Spectrum Quotient for children aged 4-11 (AQ-10 Child) questionnaire with 292 participants, incorporating both demographic and behavioral information, designed for participants or their parents to answer based on their specific situation. It consists of 292 rows and twenty-one columns. Ten columns have the answer code (either 0 or 1) for each of the ten questions in the questionnaire, capturing the answers of the participants, while the remaining eleven columns provide details about the features used in the dataset. These features include age, gender, ethnicity, jaundice history, autism diagnosis, country of residence, prior use of the app, questionnaire results, age description (age range), relationship of the respondent to the participant, and the class/target indicating whether the participant is at risk of having ASD. Each row represents individual data that contributes to the overall results of the questionnaire. It is important to note that this dataset only captures responses to the questionnaire and does not serve as a definitive diagnostic tool for autism. Table I includes all features along with their descriptions.

TABLE I. DATASET DESCRIPTION

Feature Name	Description
A1	S/he often notices small sounds when others do not (score 1 for definitely/slightly agree)
A2	S/he usually concentrates more on the whole picture, rather than the small details (score 1 for definitely/slightly disagree)
A3	In a social group, s/he can easily keep track of several different people's conversations (score 1 for definitely/slightly disagree)
A4	S/he finds it easy to go back and forth between different activities (score 1 for definitely/slightly disagree)
A5	S/he doesn't know how to keep a conversation going with his/her peers (score 1 for definitely/slightly agree)
A6	S/he is good at social chit-chat (score 1 for definitely/slightly disagree)
A7	When s/he is reading a story, s/he finds it difficult to work out the character's intentions or feelings (score 1 for definitely/slightly agree)

A8	When s/he was in preschool, s/he used to enjoy playing games involving pretending with other children (score 1 for definitely/slightly disagree)
A9	S/he finds it easy to work out what someone is thinking or feeling just by looking at their face (score 1 for definitely/slightly disagree)
A10	S/he finds it hard to make new friends (score 1 for definitely/slightly agree)
Age	How many years old the participant is
Gender	Male or Female
Ethnicity	Ethnicity of the participant
Jaundice	Whether the participant was born with jaundice
Family_ASD	Whether the immediate family member has been formally diagnosed with ASD
Country	What country the participant is a resident of
Used_app_before	Has the participant used the app before
AQ10_Total_Score	Summation of A1 to A10 scores
Age_desc	Categorizes age
Relation	How is the person taking the test related to the participant
Class/ASD (**Target**)	Whether or not the patient is at risk of having ASD (if AQ10_Total_Score is 7 or above, classified as at risk for ASD, and if AQ10_Total_Score is less than 7, classified as not at risk for ASD)

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Fig.1 shows the count of participants by Class/ASD. Fig. 2 presents the count of participants by AQ10 Total Scores. It confirms that, in this dataset, the AQ10 total scores above 6 is classified as having high risk of ASD.

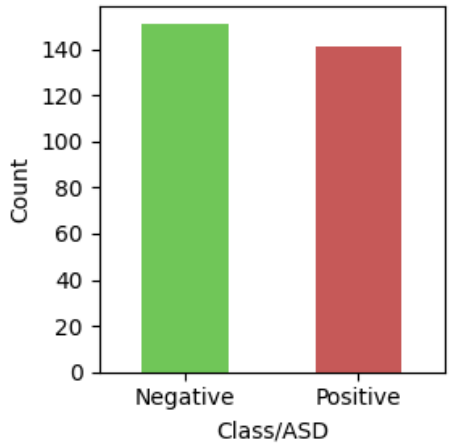

Fig. 1. Count of Participants by Class/ASD

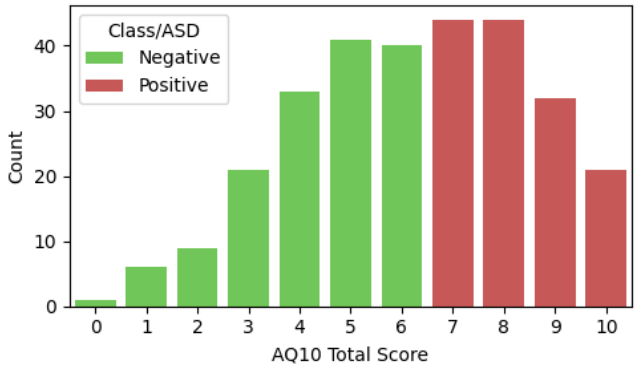

Fig. 2. Count of Participants by AQ10 Total Scores

Fig. 3 shows that the sample in this dataset has a significantly larger number of male than female in the study. This could show that there is a high potential of bias when it comes to analyzing the data.

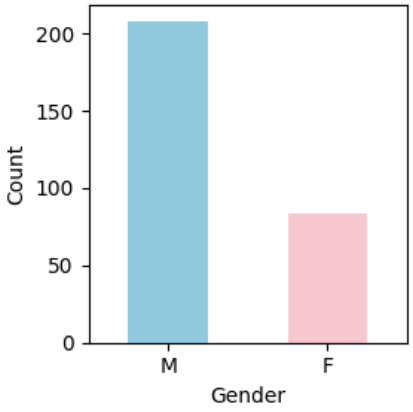

Fig. 3. Count of Participants by Gender

Fig. 4 shows a count plot of AQ10 Total Scores by gender. Fig. 5 presents a kernel density estimate (KDE) plot of Class/ASD (Positive or Negative) by gender. Comparing Fig. 4 and 5, we can observe no differences in the distribution

shapes by gender. Based on these two figures, we cannot conclude that gender is correlated with AQ10 scores.

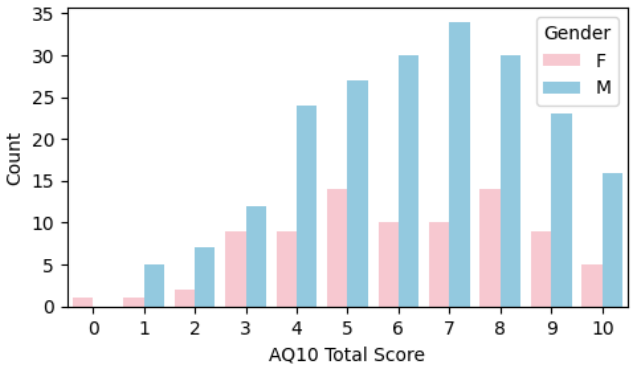

Fig. 4. Count of AQ10 Total Scores by Gender

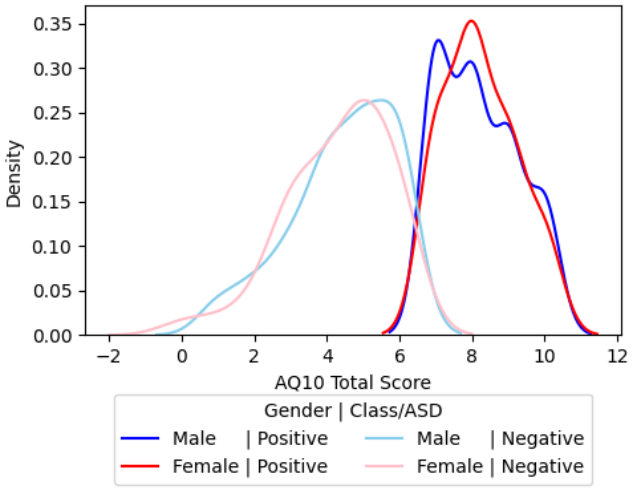

Fig. 5. Density of AQ10 Total Scores by Class/ASD and Gender

In the count plot in Fig. 6, the X-axis represents the total AQ10 score, which indicates participants' scores. The primary Y axis (y1) shows the number of participants who received each score, with green bars representing those who were not born with jaundice and red bars representing those who were born with jaundice. The secondary Y-axis (y2) displays the percentage of individuals born with jaundice at each score level, illustrated by the blue line. This combination allows us to see both the distribution of scores and the proportion of participants with jaundice at each score. The increase in percentage at lower scores could imply that jaundice has a more noticeable correlation with these lower scores, highlighting a possible link between jaundice and traits that result in low AQ10 scores. A flat trend implies that jaundice at birth does not appear to affect these higher scores in any notable way; the jaundice percentage stays roughly the same across higher AQ10 scores. In essence, the upward trend at lower scores suggests that jaundice may have more relevance or impact in people with lower AQ10 scores, whereas a flat trend at higher scores suggests that jaundice has less influence as scores increase.

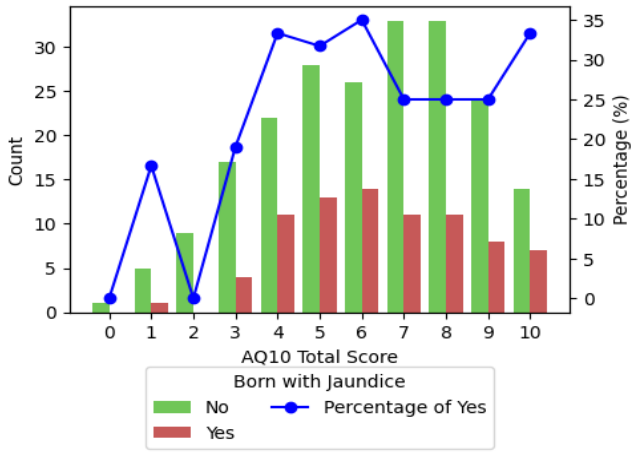

Fig. 6. Count and Percentage of AQ10 Scores by Jaundice at Birth

Fig.7 shows the density of AQ10 total score by Jaundice at Birth. The X-axis represents the AQ10 total score, while the Y-axis shows the density, indicating how scores are distributed within each group. The blue line represents participants who were not born with jaundice, and the red line represents those who were born with jaundice. This plot allows us to compare the overall shape and spread of AQ10 scores between the two groups, providing insight into whether being born with jaundice influences the distribution of scores. Since the KDE density plot lines are similar for both groups (those born with jaundice and those not), it suggests that the distribution of AQ10 scores is similar regardless of jaundice status. This similarity indicates that jaundice at birth might not be strongly correlated with AQ10 scores, which are often used as a measure for traits associated with Autism Spectrum Disorder (ASD). In other words, having similar lines implies that being born with jaundice does not appear to significantly influence or differentiate the AQ10 scores. This observation supports the hypothesis that jaundice at birth does not have a noticeable impact on ASD-related traits as measured by the AQ10 scale in this dataset.

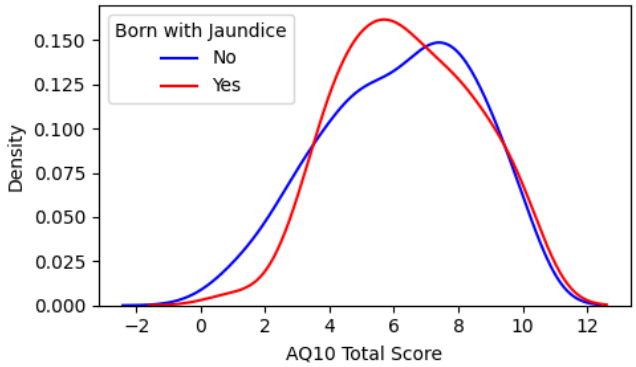

Fig. 7. Density of AQ10 Total Score by Jaundice at Birth

Fig. 8 illustrates the density distribution of AQ10 total score based on whether individuals have an immediate family member with ASD. The red curve represents those with a family history of ASD, while the blue curve represents those

without a family history of ASD. The blue curve is slightly higher and shifted to the right compared to the red curve, suggesting that individuals without a family history of ASD tend to have higher AQ10 scores on average. Conversely, the red curve's shift to the left implies that individuals with a family history of ASD are more likely to score lower on the AQ10, indicating a subtle trend. However, the significant overlap between the two curves highlights that AQ10 scores span a similar range for both groups, meaning family history alone is not a definitive predictor of ASD but may influence susceptibility.

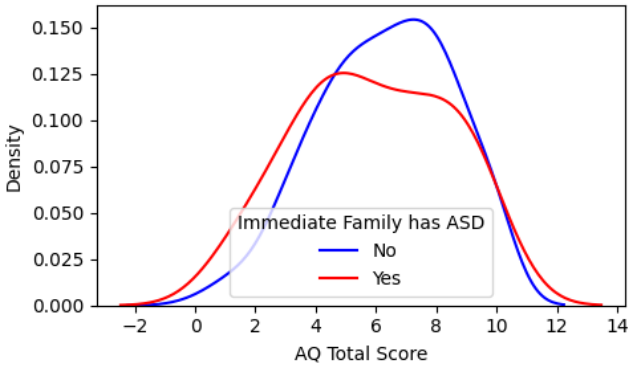

Fig. 8. Density of AQ10 Total Score Based on Whether Immediate Family Has ASD

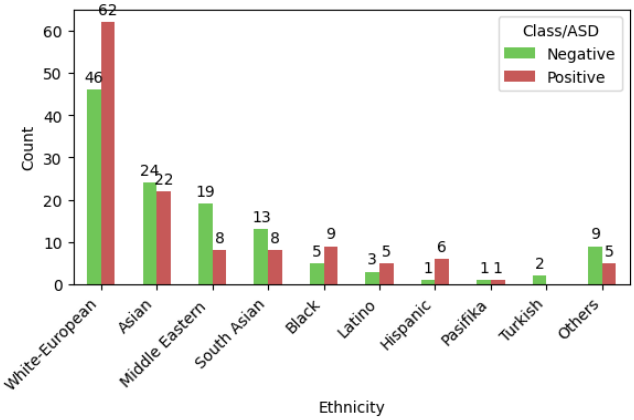

Fig. 9. Ethnicity of Participants and Class/ASD

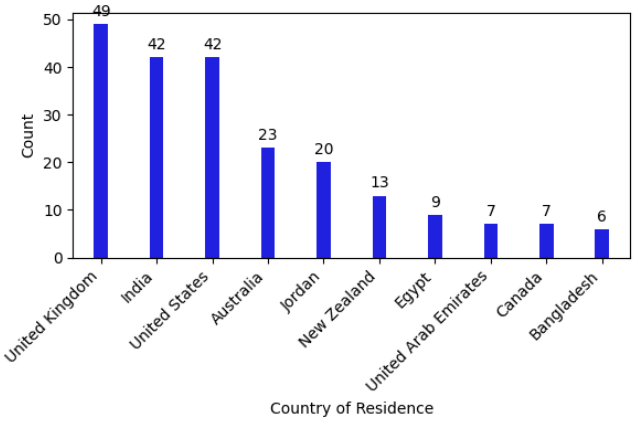

Fig. 10. Top 10 Country of Residence for Participants

Fig. 9 represents a count plot of participants' ethnicity, showing the number of individuals in each ethnic group classified as ASD-positive or ASD-negative by the AQ10-Child. Fig 10, which shows the top 10 countries of residence for participants, reveals a significant bias in the dataset towards residents from the United Kingdom, India, and the United States. These two figures indicate variability in the representation of ethnic groups within the dataset, and thus, it cannot be concluded that there is a correlation between ethnicity and AQ10 total scores.

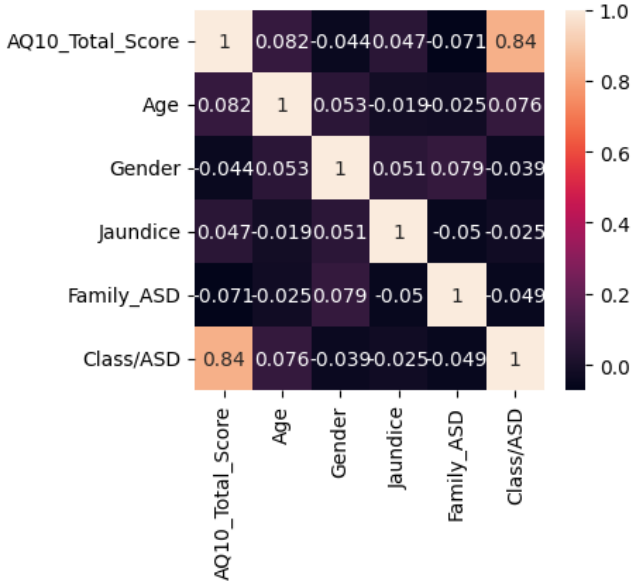

Fig. 11. Correlation Among AQ10_Total_Score, Age, Gender, Jaundice, Family_ASD, and Class/ASD

Fig. 11 represents the correlation among the variables AQ10_Total_Score, Age, Gender, Jaundice, Family_ASD, and Class/ASD. In the heatmap, a correlation coefficient close to 1 indicates a strong positive correlation, close to -1 indicates a strong negative correlation, and close to 0 indicates no correlation. The intensity of the color represents the strength of the correlation. As shown on Fig. 11, there is a correlation value of 0.84 between AQ10 Total Score and Class/ASD. Age, Gender, presence of Jaundice, and presence of ASD in the immediate family show very low values of correlation, with values below 0.1. This suggests that these variables do not have a strong association with ASD diagnosis or AQ10 scores.

V. Conclusion and Future Work

This study underscores the potential of leveraging expanded datasets, incorporating demographic, medical, and familial factors, to enhance the diagnostic process for Autism Spectrum Disorder (ASD). However, the analysis revealed that none of the examined factors, including family history of ASD, jaundice, gender, and ethnicity, showed a significant influence on ASD, likely due to the limitations imposed by the small sample size. The heatmap analysis further confirmed that there was almost no correlation between these variables and ASD, highlighting the challenges of drawing

definitive conclusions from a dataset that is not large enough to yield robust results.

In addition to the sample size issue, the dataset displayed inherent biases, including gender imbalances, which may have also influenced the ability to detect meaningful relationships. Given these limitations, future research should focus on expanding the dataset to include a larger, more diverse sample. With a more robust dataset, it would be possible to assess these variables with greater confidence and potentially identify key predictors of ASD. These future studies can contribute to a more accurate and equitable diagnostic process, ensuring that early identification of ASD leads to timely interventions that improve outcomes for affected individuals.

Furthermore, integrating advanced diagnostic tools such as machine learning and AI-driven systems could improve the precision and accuracy of ASD detection, providing a more reliable framework for early diagnosis.

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