Predicting Core Characteristics of ASD Through Facial Emotion Recognition and Eye Tracking in Youth

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***Abstract*— Autism Spectrum Disorder (ASD) is a heterogeneous neurodevelopmental disorder (NDD) with a high rate of comorbidity. The implementation of eye-tracking methodologies has informed behavioral and neurophysiological patterns of visual processing across ASD and comorbid NDDs. In this study, we propose a machine learning method to predict measures of two core ASD characteristics: impaired social interactions and communication, and restricted, repetitive, and stereotyped behaviors and interests. Our method extracts behavioral features from task performance and eye-tracking data collected during a facial emotion recognition paradigm. We achieved high regression accuracy using a Random Forest regressor trained to predict scores on the SRS-2 and RBS-R assessments; this approach may serve as a classifier for ASD diagnosis.**

I. INTRODUCTION

Autism spectrum disorder (ASD) is a complex, heterogeneous neurodevelopmental disorder (NDD) that emerges early in childhood. People with ASD have lifelong impairments in social interactions and communication, as well as restricted, repetitive, and stereotyped behaviors and interests (RRBs) [1]. Prior research has suggested that individuals with ASD process visually-presented, socially-relevant stimuli atypically, greatly impacting social cognition. Using eye-tracking (ET) technologies to track and analyze visual gaze patterns has improved our understanding of the mechanisms underlying social information processing and its significance in ASD.

Developmental differences in how individuals with ASD acquire (visual gaze patterns) and recognize (emotion identification) socially-relevant information have been reported in infancy and continue across the lifespan (Webb *et al.* [2]). Both Tang *et al.* [3] and Pelphrey *et al.* [4] reported no accuracy differences on emotion recognition tasks between adults with and without ASD; however, there was a significant difference in their information acquisition process. Individuals with ASD displayed increased fixation on areas of the screen displaying non-social information, such as objects or background stimuli. Dijkhuis *et al.* [5] combined ET data, skin conductance levels, and measures of social impairment (SRS-A) in adults with and without ASD to examine social attention and emotional responsiveness in association with autism symptom severity; higher SRS-A scores were indicative of decreased time viewing faces, regardless of diagnostic grouping. Within the ASD group, fewer fixations on faces was also related to higher symptom severity.

The core characteristic of RRBs in ASD also plays a critical role in social cognition. Research has suggested that circumscribed and highly-focused interest, a key component in RRBs, may affect social information processing by "trapping" or "capturing" an individual's attention while viewing a scene. Previous research has established that individuals with ASD display increased visual attention towards non-social and subject-specific circumscribed interest (CI) stimuli across development [6]–[9]. In contrast, Parson and Carlew [10] noted no change in performance when ASD participants were presented with subject-specific CI stimuli during a selective attention task. As such, more studies are needed to understand the role of RRBs in visual exploration of the social environment.

In this paper, we combine task performance and ET data under a facial emotion recognition paradigm, and develop a Random Forest [11] regressor to predict scores on assessments measuring social responsiveness and RRBs in typically-developing (TD) participants and in a sample of individuals with NDDs. NDDs, particularly ASD and Attention-Deficit/Hyperactivity Disorder (ADHD), are highly comorbid and have been shown to share multiple neurocognitive features with potentially overlapping underlying neurobiological mechanisms. It has been reported that 30-80% of individuals with ASD present with ADHD traits [12], [13], and it is estimated that up to 30% of individuals with ADHD present with traits of ASD [14], [15]. ADHD is characterized by behavioral symptoms of inattention and/or hyperactivity-impulsivity [1]. Atypical visual processing and impairments in emotion recognition have also been observed in ADHD [16], [17]. Investigations utilizing latent class analysis have revealed atypical social cognitive processing in individuals with NDDs [18], [19]. This mirrors findings by van der Meer *et al.* [12] that noted individuals in the comorbid (ASD and ADHD) class were less accurate and had slower response times than the other clinical groups and TD sample. Hence, we included participants with ASD and ADHD in order to gain insight into differences and

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similarities of the neuropsychological endophenotype underlying the process of emotion recognition. The inclusion of TD individuals added valuable insight into the subclinical traits distributed throughout the general population. Our experimental results show the effectiveness of applying ET and machine learning in the prediction of ASD symptom severity.

II. METHOD

A. Participants

Sixty participants were recruited through the University of Minnesota (UMN) with the approval of the UMN Institutional Review Board. Twenty-four individuals with neurodevelopmental diagnoses (F: 5; 12.13 ± 2.35 years; ASD: n=13; ASD+ADHD: n=8; ADHD: n=3) and an age-matched cohort of 36 TD individuals (F: 13; 12.50 ± 2.37 years) completed an ET task and two assessments measuring social behavior and RRB. There were no significant differences of age (t-test p=0.54) or sex (t-test p=0.21) between the two main groups (TD and NDD).

B. Task and Assessment Measures

Faces contain a wealth of social data; therefore, how faces are viewed and the processing of facial information can influence the interpretation of social interactions. We used a modified Dynamic Affect Recognition Evaluation (DARE) task [20], [21] previously described in [22]. Specifically, the DARE task used images from the Cohn-Kanade Action Unit-Coded Facial Expression database [23], [24] to create a sequence of faces that morph from neutral to one of six emotions (see Figure 1). A trial consisted of the video starting and then the participant pressing the spacebar to halt the video when they could identify the emotional expression. Upon halting the video, the participant had unlimited time to make a forced choice between six emotions (anger (1), disgust (2), fear (3), happiness (4), sadness (5), and surprise (6)) that appear on the screen. The emotions were read out to the participant and the corresponding button was pressed by the researcher.

Social Responsiveness Scale-2 (SRS-2) [25]. The SRS-2 is a 65-item, Likert scale parent-report questionnaire that measures reciprocal social behavior. The measure yields a total and five subscale scores: social awareness, ability to identify the social cues of others; social cognition, the skill to interpret social behaviors; social communication, which assesses reciprocal communication in social situations; social motivation, which measures the inclination to participate in social situations; and RRB, which measures the severity of stereotypy and CI. Higher scores reflect greater severity of social deficits.

Repetitive Behavior Scale-Revised (RBS-R) [26]. The RBS-R is a 43-item, Likert-scale parent-report questionnaire that measures the presence and severity of RRBs in ASD [26], [27]. The RBS-R yields a total and six subscale scores. The subscales include: stereotypy, defined as apparently purposeless repeated movements; self-injurious behavior (SIB), which consist of repeated actions that have

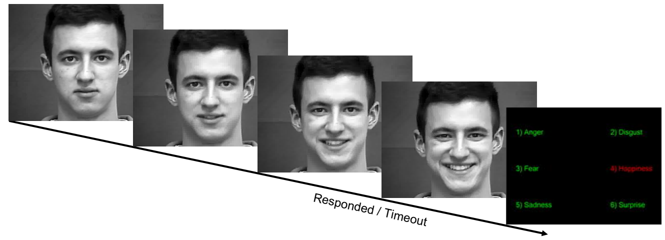

Fig. 1. The DARE task. An example displaying a face transitioning from neutral to happiness.

the potential to or actually cause bodily harm; compulsive behaviors are repeated behaviors performed according to "rules"; ritualistic behaviors that are daily routines performed in a repetitive and stereotyped manner; sameness behaviors or insistence on sameness, characterized by resistance to changes in routines or environments; and restricted behaviors, which are characterized by highly-focused interests or activity. The RBS-R was not completed for 21 participants. Therefore this analysis is a smaller subset of this study population.

C. Eye-Tracking Acquisition Procedures

The ET data were collected in the same manner as described in [22]. In detail, two acquisition systems utilizing Tobii Studio (version 3.3.2; Tobii, Stockholm, Sweden) were used to collect ET data across two collection sites. ET data were collected on the Tobii Pro TX300 (sampling rate: 300 Hz) for 24 individuals with a diagnosis and 10 TD participants. The remaining ET data (26 individuals) were collected on the Tobii X2-60 (sampling rate: 60 Hz) due to its portability. Neither the similarity in precision nor the difference in sampling speeds between the two systems factored into the analyses. A standard 9-point grid was utilized to calibrate both systems, and the calibration error was less than 0.5° along the x- or y-axis for all participants in the analyses.

D. Predicting Assessment Scores with Machine Learning

Machine learning methods have been widely accepted for analyzing eye movements as well as learning behavioral traits of ASD [22], [28], [29]. State-of-the-art deep learning algorithms have accurately classified people with and without ASD based on their gaze patterns in passive image-viewing [29]. However, these models depend on large training data, which were not available for this study. Instead, our analysis focused on the correlational analysis between various features and the assessments of ASD traits that distribute continuously across all participant groups. We further developed a regression model based on our observations to predict the assessments.

Figure 2 presents the statistics of three basic behavioral measures: response time (RT), percent correct (Correct %), and number of fixations (N. Fixations). Pearson's correlation analyses showed a strong correlation between RT and SRS-2 ($p < 0.001$), as well as between RT and RBS-R (p=0.014).

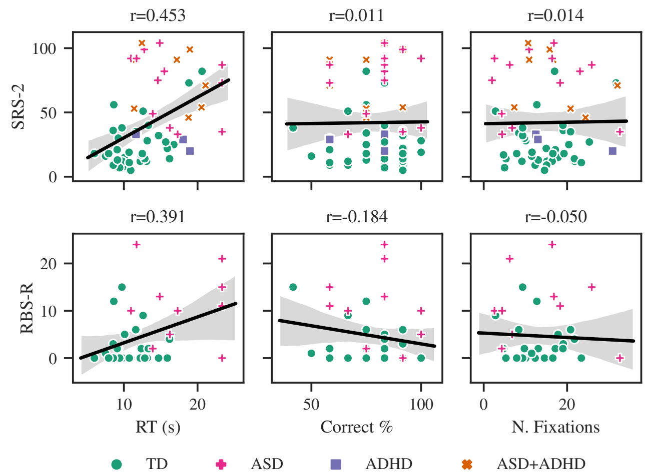

Fig. 2. Statistics of the behavioral performances in the DARE task and their correlations (Pearson's r) with the SRS-2 and RBS-R assessments. Lines and shades indicate linear fits and 95% CI.

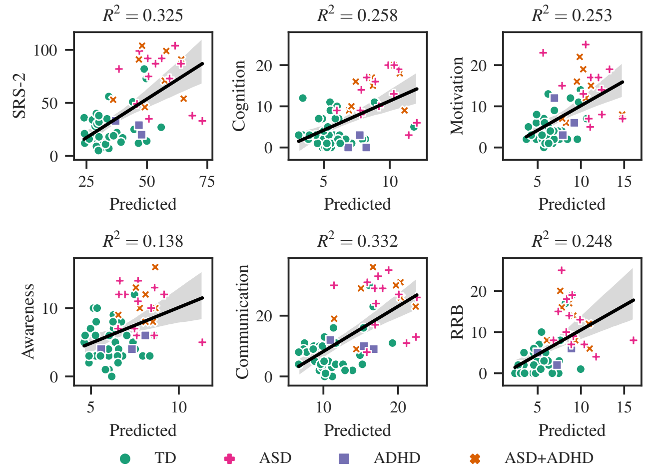

Fig. 3. Prediction results for the SRS-2 total and subscale scores. Lines and shades indicate linear fits and 95% CI.

Emotion recognition accuracy was not significantly correlated with either assessment (both ps>0.25). The number of eye fixations were also not correlated with the assessments (both ps>0.75). Therefore, we represented the facial emotion recognition performance as a two-dimensional feature vector including the RT and relative RT that was normalized with the length of each video.

We also observed differences in the spatial distributions of eye fixations (data not shown). The distributions were represented as a fixation map computed for each trial. To compute the fixation map, we uniformly divided the face region into 6×6 bins and counted the number of fixations in each bin. We created a fixation map of 6×6 pixels where each pixel value represents the density of fixations in the corresponding bin, and normalized the map to the sum of one. Finally, the map was smoothed with a Gaussian kernel ($\sigma = 0.5$). Aggregating the fixations of participants in each group, data showed that participants diagnosed with ASD had higher fixation density on the background and decreased gazing toward the eye region, consistent with Tang *et al.* [3].

Based on these observations, for each trial we converted its fixation map into a 36-dimensional feature vector and concatenated it with the task features. We performed a principle component analysis (PCA) to transform the combined features into a 16-dimensional vector. With these features, a Random Forest regressor was trained to predict the assessments and subscales of the corresponding participant. We applied a leave-one-out cross-validation to train and evaluate the regressor. In each run, data from one participant were left out as testing data, while the rest were used for training. The test results were averaged across all trials of the same participant. This process was repeated 60 times so that each participant was tested once. All testing results were combined and evaluated using an R^2 measure.

III. RESULTS

As noted above, relationships between assessments measuring symptoms of ASD and visual processing have been observed. Once thought of as a categorical diagnosis, we now know that ASD traits are continuously distributed throughout the general population. Therefore, we investigated our experimental results both categorically (ASD and ASD+ADHD v. TD and ADHD) and along a continuum (SRS-2 and RBS-R scores).

We trained and evaluated models to predict the total SRS-2 and its subscales independently. Figure 3 shows a high prediction accuracy ($R^2 = 0.325$) on the SRS-2 total score. High prediction accuracy is also found in the Social Cognition, Social Motivation, Social Communication, and RRB subscales. Figure 3 also shows a good separation between participants with and without ASD. The models predicted higher SRS-2 scores for the ASD and ASD+ADHD participants, but lower scores for the TD controls. While the sample size is limited, moderate scores for the ADHD participants were noted. This observation agrees with the previous findings of Miller *et al.* [30].

For the RBS-R prediction (see Figure 4), the model performed accurately on the total score with $R^2 = 0.302$, but not the subscales, which is likely due to the smaller sample size of the RBS-R data. It is noteworthy that the predicted scores are better at separating ASD participants from TD controls than the observed RBS-R assessments, suggesting that our method is potentially a more robust and objective

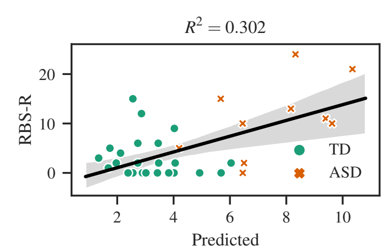

Fig. 4. Prediction results for the RBS-R total score. Lines and shades indicate linear fits and 95% CI.

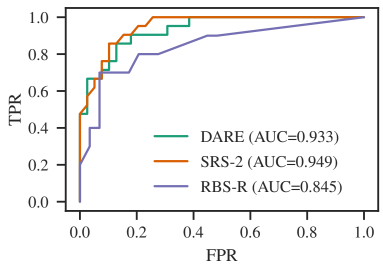

Fig. 5. ROC curves for ASD classification.

measurement of ASD traits.

To test how the regression model could benefit ASD diagnosis, we conducted ROC analysis and computed the area under the ROC curve (AUC) for the proposed method, and compared it with the two assessments. Figure 5 shows comparable AUC scores between the DARE ET task and the ASD assessments, which suggests that participants' performance data and gaze strategies in the DARE task can make a good classifier even without supervision from the diagnostic labels. Therefore, combining data from objective methodologies such as ET and quick, simple, yet subjective assessments can aid in the classification of ASD.

IV. DISCUSSION AND FUTURE WORK

In the present study, we built a model based on features from an emotion recognition task in an effort to predict scores on assessments measuring the two core characteristics of ASD: social impairments as measured by the SRS-2 and RRBs as measured by the RBS-R. Both the SRS-2 and the RBS-R total scores were well predicted by our model. Our results demonstrating a strong relationship between assessment scores and a model constructed around a social cognition task align well with previous research [5], [6], [31].

Future investigations should increase sample size and include a broader age distribution. Given prior reports of age effects in similar tasks, evaluating the results across a wider age range would provide an opportunity to detect possible patterns of change throughout development [32]. Including a more even ratio of male and female participants would allow for the investigation of sex differences, as both disorders show a higher prevalence in males (ADHD 10-3:1 [33]; ASD 4.5:1 [34]). Furthermore, as noted above, ASD is a heterogeneous disorder with varied presentation and high clinical overlap with other NDDs. Hence, increasing the ASD sample will also increase our ability to identify ASD endophenotypes. Norbury and colleagues [31] showed that, regardless of language phenotype (normal or impaired language), ASD individuals that viewed the mouth region longer had better adaptive communication outcomes and increased fixation on the eye region was associated with a decrease in adaptive communication. Our data suggest that combining machine learning methods with behavioral assessments and ET data has the potential to improve detailed classification of individuals with multiple diagnoses; thus, augmenting the sample of individuals with comorbidities is also indicated. Additionally, including individuals with diagnoses of other psychiatric disorders can lead to potential early detection of comorbid disorders [35]. Other methodological factors to consider are the selected assessment and task measures, as the assessment reporter (clinician, caregiver, or self) may be an influential factor on scores. Alternate task designs should also be explored to improve the generalizability of the model since task features such as static versus dynamic images, or the complexity of social interactions displayed, can influence the results of ET studies [36]. Continued research to elucidate the link between viewing patterns and atypical social interactions in ASD, and NDDs more broadly, will improve diagnostic accuracy and help identify novel treatment targets. The integrative approach of combining task data and objective measures such as ET and autonomic responses with machine learning techniques is highly promising as a means to uncover these links.

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