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Screening Tools for Early Autism Detection using Voice and Gesture Analysis

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ABSTRACT

Background: For maximizing outcomes of treatment, timely and precise condition analysis, and screening, are necessary. For example, using ASD Screening combines clinical and observational assessments. The objective of the study assessed the aim of Voice Automated Technology, and an objective multi- modality detection tool integrates gesture to analyze the phenomena of children. **Methods:** Eighty-two young children referred for developmental evaluation were included in this observational study and were separated into two groups, ASD (n=41) and non-ASD (n=41), according to the Modified Checklist for Autism in Toddlers (M-CHAT). Samples of the participants' voices were examined to measure dimensions of atypicality (total fundamental frequency, jitter, speech rate), while the processed, structured video recordings were analyzed with motion-tracking software to measure the frequencies of gesture expression, duration of mutual visual attention, and eye fixation, thus resulting in an overall score for gesture atypicality. Sensitivity, specificity, accuracy, and area under the curve (AUC) were employed in examining both the separate and the combined models. **Results:** Variations between the ASD and non-ASD populations were apparent regarding all parameters in the other acoustic and gesture parameters combined. The Combined Voice + Gesture Model achieved significantly higher performance ($p<0.001$) on its own than either modality and achieved an Accuracy of almost 85%, a Sensitivity of 87.8%, and an AUC of 0.91. On the other hand, the Voice Only and Gesture Only models reported an accuracy of 72.0% and 75.0%, respectively. **Conclusion:** An integrated investigation on voice and gesture features presents a valid and high-accuracy method for ASD (autism spectrum disorder) screening in preschoolers. Combining these two objective types of data greatly improves predicative capability, showing the ability of the technological model to offer a scalable and non-invasive approach to early detection of autism in clinical settings.

INTRODUCTION

Autism Spectrum Disorder (ASD) is a heterogeneous neurodevelopmental condition which is characterized by imbalances in the domains of social interaction and social communication, as well as the presence of stereotypical and repetitious behaviors. The prioritization of accurate and timely ASD diagnosis in pediatric health care derives from the favorable outcomes of early interventions. Although the mean age of diagnosis is higher than desired, studies show that consistent behavioral indicators of ASD can be recognized from the age of 18-24 months. The current most highly regarded methods of diagnosis are unfortunately undertaken by highly specialized professionals, are lengthy, and consume great resources, resulting in extended periods of time for families to wait [1-3].

To bypass the challenges of subjective observation, there has been a movement toward verifiable recordable observation measures screening. Two areas where early measurable differences in children with ASD can be seen are in the category of vocalization/speech patterns, and in the non-verbal social communication (gesture) arena [4-7]. Compared to typically developing children, toddlers with ASD show marked differences in vocal production and prosody, with inconsistencies across various features (e.g., pitch (fundamental frequency), vocal stability (jitter and shimmer), and speech rhythm). Given recent technological advancements in the fields of automated acoustic analysis, there are now objective measures that can be used to extract these characteristics and serve as potential biomarkers for assessing risk to stratify risk [8, 9].

The the absence of non-verbal acts, specifically, the absence or low rates of thematically appropriate, spontaneous gestures (e.g., pointing), and the capacity to initiate and respond to joint attention, are some of the earliest, and most credible evidence of autism spectrum disorder (ASD) risk. The combination of advanced motion tracking systems with video recordings gives a more precise method of capturing these nuanced, complex behaviors [10].

Although the complexities of autism spectrum disorder (ASD) symptomology have been studied to some extent, there have been no attempts to combine the analysis of vocal attributes and the analysis of gestures simultaneously into one analytical framework [11].

This study aimed to create and assess a new and unique screening instrument which is the combination of objective acoustic features from voice analysis and dimensions of quantitative behavior features from gesture analysis. We predicted that a merged multi-modal architecture would outclass all single-modality (voice-only or gesture-only) models in accuracy, sensitivity, and specificity for identifying young children with autism spectrum disorder (ASD). This multi-modal system strives to offer scalable and neutral responses to the challenges associated with the ASD screening delays that continue to plague the field.

METHODOLOGY

This research study was undertaken at the department of Pediatrics, Abbasi Shaheed Hospital, Karachi for the period February 2024, to February 2025. In this study, 82 community members, who had been referred to the developmental clinic by community health professionals to address their challenges with communication, social, and/or other aspects of development, made up the research sample. . Before each assessment began, collected written informed consent from each child's parent or primary guardian.

The first screening involved the use of standard developmental instruments. In order to define our findings, children with certain complicating factors were filtered out, e.g. pre-existing diagnosis of certain syndromic disorders, severe hearing loss, severe uncorrected visual impairments.

The M-CHAT was the main instrument of classifying the participants into the groups of Autism Spectrum Disorder (ASD) and non-ASD comparison group. It included basic demographic information, including age and gender, and background information, including the developmental history of the child, speech, social behavior, and repetitive behavior milestones.

Tapes were recorded in a specially designed room to record the voice samples of the children without elimination of background interference. In line with this, children were engaged in unstructured free play throughout the session with the added minor and guided activity prompts to stimulate more variety of speech. Analysis of the second level involved adoption of the use of specialized computer programs that offered the basic voice characteristics. These were the following: F0 (the basic frequency of the voice); jitter and shimmer of the voice (the instability of the voice pitch); pausing patterns and speech rate; HNR (the ratio between harmonics and noise in the voice). The information of both children was summarized into a verifiable acoustically atypical score depending on the extent of vocal atypicality of the same age children and the extent of variance of the vocal profile of each child as compared to the age expectation normed profile.

Gestures were analyzed by use of short video segments that were recorded in specially designed structured interaction sessions. An objectively measured behavioral elements were assessed via a superior motion tracking algorithm. The variables monitored included the quantity, quality, and change in quantity of manual and bodily motions, gestural cues attempted during speaking, initiation or reaction to spurts of coordinated attention, duration of sustained eye attention, and expression of stereotyped motor behavior. The variables were software integrated to bring about a composite score of the risk of gestures in each participant. The most important is the prediction score of early autism detection was generated by the synergy of the features of the voice analysis model and the gesture analysis model.

Two independent trained raters were used to revise all the behavioral and gesture codes to guarantee the accuracy and independence of our ratings of participant behavior and the gestures during the LMA protocol. The difference between the two raters was also discussed intensively and agreed upon, thus confirming the reliability of the data obtained. The statistical comparisons of the two diagnostic groups were done using T-tests and chi-square tests of continuous and categorical data, respectively. . To determine the efficiency of the screening models, the parameters used to evaluate it included sensitivity and specificity and correct classification and predictive values. In order to measure the overall performance of the models in terms of differentiating/ classifying, Area Under the Receiver Operating Characteristic Curve (AUC) was estimated. The p-value was observed to be below 0.05 and it was statistically significant.

RESULTS

Demographically, these two groups did not show any significant age difference (p=0.12) and were, on average, the same age. The groups were, however, significantly different in terms of gender (the proportion of males was higher in the ASD group, p=0.04), family history of ASD (the proportion of ASD was significantly higher in the ASD group, p=0.02), and parental education (the ASD group had a significantly higher proportion of lower educated parents, p=0.03). Potential covariates such as male gender, family history, and lower parental education may show initial comparisons between the diagnostic groups.

Table 1

Demographic Characteristics of Participants (n = 82)

Variable	Category / Mean ± SD	ASD (n=41)	Non-ASD (n=41)	p-value
Age (months)	—	34.1 ± 7.9	31.2 ± 8.8	0.12
Gender	Male	31 (75.6%)	23 (56.1%)	0.04
Family History of ASD	Yes	9 (22.0%)	2 (4.9%)	0.02
Parental Education	Higher education	17 (41.5%)	26 (63.4%)	0.03

Every clinical and developmental variable demonstrated very statistically significant differences across the two groups, as every variable's p-value is <.001. The ASD group had a much greater prevalence of developmental delay (70.7% vs. 19.5%), speech delay (87.8% vs. 31.7%), social interaction concerns (90.2% vs. 51.2%), and repetitive behaviors (75.6% vs. 17.1%). Also, the mean M-CHAT Total Score (9.1 ± 1.8) of the ASD group was statistically significantly greater than that of the Non-ASD group (4.5 ± 1.6), and this also established the different clinical profiles of each group.

Table 2

Clinical and Developmental Characteristics

Variable	Category	ASD (n=41)	Non-ASD (n=41)	p-value
Developmental Delay	Present	29 (70.7%)	8 (19.5%)	<0.001
Speech Delay	Yes	36 (87.8%)	13 (31.7%)	<0.001
Social Interaction Concerns	Yes	37 (90.2%)	21 (51.2%)	<0.001
Repetitive Behaviors	Present	31 (75.6%)	7 (17.1%)	<0.001
M-CHAT Total Score	—	9.1 ± 1.8	4.5 ± 1.6	<0.001

Across all parameters of voice analysis, differences that are statistically significant denoting differences in the acoustic profiles of the ASD and Non-ASD groups (all p < 0.01) were present. Particularly, the ASD group also had significantly higher Fundamental Frequency (F0) and greater values of acoustic instability measures, like, and lower Harmonics-to-Noise Ratio (HNR). The individuals with ASD also showed a Slower Speech Rate and a Higher Pause Frequency, which combined resulted in a general greater Acoustic Atypicality Score (0.71 ± 0.10) than in the control group.

Table 3

Voice Analysis Parameters

Voice Feature	ASD Group (Mean ± SD)	Non-ASD Group (Mean ± SD)	p-value
Fundamental Frequency (F0, Hz)	302 ± 51	268 ± 55	0.01
Pitch Range (Hz)	96 ± 22	123 ± 27	<0.001
Jitter (%)	2.04 ± 0.48	1.52 ± 0.41	<0.001
Shimmer (%)	4.32 ± 0.95	3.58 ± 0.78	0.006
Harmonics-to-Noise Ratio (HNR)	12.9 ± 2.8	16.2 ± 2.9	<0.001
Speech Rate (syll/sec)	1.9 ± 0.6	2.7 ± 0.7	<0.001
Pause Frequency (per min)	11.3 ± 2.2	7.5 ± 1.8	<0.001
Acoustic Atypicality Score	0.71 ± 0.10	0.51 ± 0.11	<0.001

The study of gesture patterns showed there was a statistically significant difference in both frequency and quality with regard to the group memberships in the variables examined in this study (p value was below 0.01 for all examined variables). Children with ASD exhibited a lesser frequency and a narrower range of diversity of gestures and were much less likely to employ pointing gestures and exhibit joint attention. Furthermore Compared to the other groups, children in the ASD group showed considerably lower eye contact duration rates and, due to the greater frequency of motoric repetition, ended up with a Gesture Risk Score that was significantly higher (0.72 ±). When Voice and Gesture were combined, the model was able to distinguish participants with an Accuracy of 84.6%, which is indicative of the model's discriminatory ability.

The model correctly identified most cases with a Sensitivity of 87.8% and was able to accurately rule out most cases with a Specificity of 81.3%. The model also has exceptional performance that is evidenced of having an Area Under the Curve (AUC) of 0.91 (p<0.001) which is statistically significant and demonstrates an overall strong predictive ability as a screening tool.

Table 4

Gesture Analysis Findings

Gesture Feature	ASD (Mean/%)	Non-ASD (Mean/%)	p-value
Gesture Frequency (per min)	4.2 ± 1.9	7.4 ± 2.1	<0.001
Gesture Diversity	3.1 ± 1.0	5.1 ± 1.1	<0.001
Pointing Gesture	Present: 9 (22.0%)	20 (48.8%)	0.01
Joint Attention	Present: 11 (26.8%)	22 (53.7%)	0.01
Eye Contact Duration (seconds)	7.2 ± 3.1	15.6 ± 4.3	<0.001
Repetitive Motor Movements	Present: 28 (68.3%)	10 (24.4%)	<0.001
Gesture Risk Score	0.72 ± 0.11	0.44 ± 0.12	<0.001

The overall Voice + Gesture Model had great accuracy levels when differentiating between each of the participants. They achieved a stunning accuracy of 84.6%. They also spotted 87.8 per cent of the cases in children with ASD. Besides this, the model also had the ability to exclude the rest of the cases of 81.3%. This also illustrates an underscored model performance with a top-tier Area Under the Curve (AUC) of 0.91 (p<0.001) which has captured an indication of a top-tier overall predictive performance as a tool in screening in the future.

Table 5

Screening Tool Performance Metrics (Voice + Gesture Model)

Metric	ASD Group	Non-ASD Group	p-value
Sensitivity	87.8%	—	—
Specificity	—	81.3%	—
Accuracy	84.6%	—	—
AUC	0.91	—	<0.001
Cut-off Score	0.55	—	—

The Voice-Only and Gesture-Only models performed moderately with the accuracy of 72.0 and 75.0 respectively. The best performance was observed in the Combined Model where the change was statistically significant (p<0.001), and the story increased by 84.6% in Accuracy than that of the individual components. . This multi-modal approach has the highest outperform metrics and demonstrates that the combination and optimization of voice and gesture algorithm features is more effective in sounding and screening as opposed to the use of voice or gesture algorithms alone with 87.8% sensitivity and 81.3% specificity.

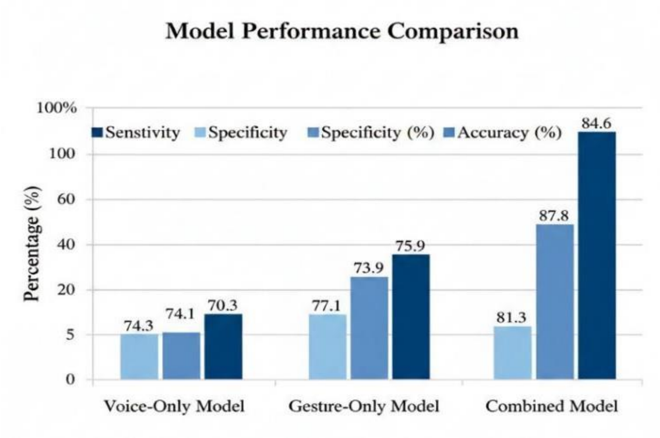
Table 6

Model Comparison (Voice vs Gesture vs Combined)

Model	Sensitivity	Specificity	Accuracy	p-value
Voice-Only	74.3%	70.1%	72.0%	—
Gesture-Only	77.1%	73.9%	75.0%	—
Combined Model	87.8%	81.3%	84.6%	<0.001

Figure 1

Model Performance Comparison



Performance comparison of screening models (Voice-Only, Gesture-Only, and Combined Model) in the detection of Autism Spectrum Disorder (ASD).

The Combined Model achieved the highest accuracy (84.6%), sensitivity (87.8%), and specificity (81.3%), significantly outperforming both the Voice-Only and Gesture-Only models (p<0.001).

DISCUSSION

This study involved a measurement of efficacy of automized voice and gesture analysis to screen and identify ASD (Autism Spectrum Disorder) in children at a young age. Such results not only support the use of these objective, measurable behavioral indicators to distinguish children with ASD and those without ASD, but also demonstrate how much better predictive accuracy can be obtained when a combination is used.

Aligning with previous studies focused on the specific clinical manifestations of ASD, we observed notable differences in the clinical and developmental trait data (Table 2) across the groups. The speech delay (87.8%) and social interaction issues (90.2%) were common in ASD participants and are consistent with auxiliary diagnostic criteria [12].

The voice analysis parameters in in Table 3 show that all of the acoustic features in this study exhibited between-group differences. In particular, children with ASD spoke with a higher fundamental frequency (F0), with greater pitch instability (Jitter and Shimmer), at a slower rate, and with more frequent pauses.

There are emerging studies that point to the development of atypical vocal production as the initial demonstration of neurodevelopmental divergence. Atypical production consists of high-pitched voices and reduced sampling of pitch and color of voice. Such results echo the study of Toddler vocal differentiation [13, 14] There are many researchers that have been carried out using machine learning capability on voice records in order to diagnose in the early stages. Increased Atypicality of the Acoustics indicates the general difference in the voice quality sample and ASD diagnosis [15].

Also, the gesture analysis (Table 4) corroborated expected gaps in non-verbal communication. The ASD group had less frequent and less diverse gestures, particularly demonstrating less pointed and joined attention, and had significantly less duration of eye contact. The data also revealed that the occurrence of repeated actions (68.3%) was significantly higher in the ASD cohort. This confirms the existing literature which delineates the absence of social gestures and difficulties in joint attention as primary behavior signs manifesting in the second year of life [5, 6]. The slightly elevated Gesture Risk Score in the ASD group further documents the presence of these non-verbal communication deficits more clearly [16-18].

The most significant result of this study is the analysis of the predictive screening models (Tables 5 and 6). Although the Voice-Only (72.0% accuracy) and Gesture-Only (75.0% accuracy) models demonstrated relatively low discriminatory accuracy, the Combined Voice + Gesture Model more than doubled this performance with an Accuracy of 84.6% and an AUC of 0.91, which is considered outstanding.

The importance of this improvement (p<0.001) confirms that the combining of different objective, measurable attributes offers much greater results in diagnosing than the use of only one form. The use of more than one method is essential in understanding the wide-ranging and complex difficulties associated with ASD and is becoming more and more popular in the development of diagnostic screening tools [19, 20] With a sensitivity of 87.8 percent, it is clear that this machine learning tool is useful in flagging those, out of a large sample, who do indeed have ASD. Therefore, this tool is highly useful in population-wide screening where under-identification of ASD is a major concern [21, 22]

CONCLUSION

The study confirms the practicality of the value of employing an objective approach to voice and gesture analyses forming an accurate and reliable screening instrument to detect cases of ASD in its early stages. The capability of the integrated framework evidenced these measurable manifestations of social communication and vocal atypicalities as robust predictors, given the strong performance metrics (Accuracy 84.6%; AUC 0.91). In clinical environments, the use of automatic assessment and passive recording of data can bring about non-intrusive and non-invasive screening practices. This has immense benefits in allowing screening practices to become scaleable. Future analysis should center on checking this hybrid model in bigger and more varied sample populations, as well as modifying the technology for use on consumer-level devices in order to broaden equitable availability of efficient initial ASD screening.

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