

Brainwave Analysis for Autism Detection: A Transfer Learning Approach

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Abstract: *Autism Spectrum Disorder (ASD) is a complex neuro developmental condition characterized by challenges in social interaction, communication, and restricted or repetitive behaviours. Early diagnosis and intervention are crucial for improving outcomes, yet ASD diagnosis remains a multifaceted process that can be challenging due to its heterogeneity and overlapping symptoms with other developmental disorders. In recent years, there has been growing interest in leveraging advanced technologies, particularly machine learning, to enhance ASD detection and improve user accessibility in diagnosis and management. This paper explores the integration of multimodal data, including genetic, neuroimaging, behavioural, and environmental factors, with deep learning algorithms to develop more accurate and efficient diagnostic tools for ASD. By combining information from diverse sources, researchers and clinicians can gain a comprehensive understanding of the underlying medical, facial factors contributing to ASD, thereby enabling earlier detection and personalized treatment approaches. Furthermore, the concept of user accessibility is integral to addressing the diverse needs of individuals with ASD and their families throughout the diagnostic process. In this we can input the three types of datasets which includes Brain MRI, Face photos and real time face streaming data. Then build the model file for each dataset by using deep learning algorithm named as Convolutional neural network algorithm to improve the accuracy in autism detection*

Keywords: Autism spectrum disorder, Deep learning, Convolutional neural network, Disease prediction, Real time face recognition, Grassmann algorithm

I. INTRODUCTION

Autism, or autism spectrum disorder (ASD), is a complex neuro developmental condition characterized by challenges in social interaction, communication, and restricted or repetitive behaviours. The term "spectrum" reflects the wide variation in challenges and strengths that individuals with autism may experience. ASD affects people of all races, ethnicities, and socioeconomic backgrounds, and it is estimated to occur in about 1 in 54 children, according to the Centres for Disease Control and Prevention (CDC). Symptoms of ASD typically appear in early childhood, often before the age of three. However, the severity and presentation of symptoms can vary widely from person to person. Some individuals with ASD may have significant cognitive impairments and require intensive support in their daily lives, while others may have average or above-average intelligence and excel in certain areas, such as mathematics, music, or art.

Key features of autism include:

- **Social Interaction Challenges:** Difficulty in understanding and responding to social cues, such as making eye contact, interpreting facial expressions, and understanding gestures. Individuals with ASD may struggle with forming and maintaining relationships and may prefer solitary activities.
- **Communication Difficulties:** Difficulty in verbal and nonverbal communication, including delayed language development, repetitive language or speech patterns (echolalia), and difficulty in initiating or sustaining conversations.



- **Restricted and Repetitive Behaviors:** Engaging in repetitive movements or behaviors, such as hand-flapping, rocking, or lining up objects. Individuals with ASD may also develop intense interests in specific topics and adhere to rigid routines or rituals.
- **Sensory Sensitivities:** Heightened sensitivity or hypo-sensitivity to sensory stimuli, such as light, sound, touch, taste, or smell. This can result in sensory overload or avoidance behaviors in certain environments. Diagnosis of ASD typically involves comprehensive evaluations by healthcare professionals, including developmental pediatricians, child psychologists, or psychiatrists. There is no single medical test to diagnose ASD; instead, diagnosis relies on a thorough assessment of a child's developmental history, behavior, and social communication skills. Early intervention services, such as behavioral therapy, speech therapy, occupational therapy, and educational support, play a crucial role in supporting individuals with ASD and their families. While there is currently no cure for autism, early intervention and appropriate support services can greatly improve outcomes and quality of life for individuals with ASD. Research into the causes of autism is ongoing, with evidence suggesting a complex interplay of genetic, environmental, and neurological factors. Advances in genetics, neuroimaging, and other fields continue to deepen our understanding of autism and inform the development of targeted interventions and treatments.
- **Performance Optimization:** Inadequate resource allocation can lead to uneven distribution of workloads, resulting in longer response times and degraded system performance. Advanced load balancing algorithms can dynamically allocate resources based on real-time monitoring and predictive analytics, thus enhancing the overall responsiveness and throughput of cloud services.
- **Scalability and Flexibility:** Cloud environments are designed to scale resources on-demand. Traditional load balancing techniques struggle to adapt to the dynamic nature of these environments, which often require rapid provisioning and deprovisioning of resources. Advanced algorithms can provide the needed flexibility to seamlessly allocate and deallocate resources, ensuring efficient scaling.
- **Heterogeneous Workloads:** Cloud platforms host a diverse range of applications with varying resource requirements. Customizing resource allocation strategies for different types of workloads is challenging. Advanced load balancing algorithms can account for these differences, ensuring that each workload receives the necessary resources to perform optimally.
- **Energy Efficiency:** Minimizing energy consumption is a critical concern for both economic and environmental reasons. By intelligently distributing workloads and consolidating tasks on fewer resources, advanced load balancing algorithms can contribute to reduced energy consumption, aligning with the principles of green computing.
- **User Satisfaction:** Cloud services cater to a wide range of users with diverse needs. An effective load balancing strategy can contribute to improved user experiences by ensuring prompt response times and efficient service delivery.

II. RELATED WORKS

Nikhil J. Dhinagar, et.al,..[1] processed a method that we term, site diagnostic meta-learning, a framework for ASD classification using structural brain MRI scans. We show the potential to accommodate multi-site heterogeneity using our meta learning approach. Our experiments show that this method used in a few-shot learning context could be useful in neuroimaging applications with limited data availability. Typically, in limited data settings, transfer learning is the preferred solution to fine-tune large pre-trained models for a downstream task. In our experiments, our proposed method based on meta-learning outperformed our transfer learning baseline in a few-shot setting, with a 24% improvement in the ROC-AUC. Our method achieved this performance when fine-tuned on only 20 samples per site. Our approach also outperformed the baseline by a 6% increase in the ROC-AUC given an independent single site dataset in zero-shot setting, i.e., without requiring any additional fine-tuning. For the meta-learning framework, we used a batch size of 1, a cosine learning rate schedule, Adam optimizer with weight decay of $1e-4$ for site-agnostic learning and Stochastic Gradient-Descent-Learning-Rule Optimizer for tuning the per-layer learnable learning rates.



D Byrne, et.al,...[2] study did not show a yield for MRI in the routine investigations of ASD without high-risk clinical features which suggest an underlying diagnosis. The decision to arrange brain MRI should be made on a case-by-case basis following careful evaluation of potential risks and benefits. The impact of any findings on the management course of the child should be considered prior to arranging imaging. And studied children with ASD, we were not able to determine the prevalence of similar brain MRI findings in our general child population. The significance of brain MRI findings was determined based on the opinion of the reporting radiologist which may be subjective. The indications for neuroimaging were recorded from radiology requests, logged in free text. Indications not listed in the request were presumed absent. This may be sensitive to documentation bias. The degree of severity of some presentations such as developmental delay could not be determined. Binary logistic regression was employed to analyse the relationship between developmental delay, epilepsy, behavioural problems, abnormal neurology, metabolic or genetic abnormality, ASD alone, macrocephaly, atypical regression, high risk history, microcephaly, headache/vomiting, and other abnormal MRI. Chi-square test was used to calculate p values for baseline characteristics.

Hidir Selcuk Nogay, et.al,...[3] All studies on automatic diagnosis of ASD with artificial intelligence are binary classification studies. An octal classification study that takes both age and gender factors into consideration cannot be found in the literature. In this study, a deep learning system that is different from what has been done so far and is a first, as far as we know, makes quadruple and eightfold classifications by taking age and gender factors into account and uses sMRI brain images. In this study, an estimation and classification system were designed, which, as far as we know, is different from what has been done so far, and which is a first, takes into account age and gender factors and utilizes sMRI brain images. The success and reliability of the designed system were provided by comparing it with the Alexnet, Googlenet, Resnet-18, and Squeezenet popular pre-trained networks. The model developed in this research performs better than these pre-trained models. In addition, the designed system has the feature of generalizability since the data set was acquired from the ABIDE database created by acquiring from 29 different locations, and the data set was enlarged five times by DA techniques. As a result, the accuracy rates acquired as a result of the test performed with all three CNN models designed to be utilized within the system show that the designed system has robust dynamics enough to give the highest accuracy rates.

Dimas Chaerul Ekty Saputra, et.al,...[4]. Autism, or Autism Spectrum Disorder (ASD), is a developmental disorder in children that causes impaired communication and socialization skills in children. Until now, the cause of autism is not known with certainty. However, the risk of developing autism disorders can increase if genetic and environmental factors include exposure to toxins, cigarette smoke, infections, drug side effects, and the mother's unhealthy lifestyle during pregnancy. Autism spectrum disorder (ASD) is a developmental disability resulting from neurological disparities. People with ASD frequently struggle with communication, social interaction, and limited or repetitive interests or behaviours. People with ASD may also have unique learning, movement, and attention styles. People living with ASD can be interpreted as 1 in every 100 individuals in the globe having ASD. The abilities and requirements of autistic individuals vary and may change over time. Some autistic individuals can live independently, while others have severe disabilities and require lifelong care and support. Autism frequently interferes with educational and employment opportunities. Additionally, the demands placed on families providing care and assistance can be substantial. Important determinants of the quality of life for persons with autism are the community's attitudes and the level of support provided by local and national authorities. Autism is frequently not diagnosed until adolescence, even though autistic traits are detectable in early infancy.

Francesco Pizzolorusso, et.al,...[5] autism spectrum disorders (ASDs) are a group of heterogeneous neurodevelopmental conditions, characterised by early onset difficulties in social communication and unusually restricted, repetitive behaviour and interests. Therefore, ASDs can severely disrupts social and cognitive functions. The prevalence of autism is constantly increasing compared to the first epidemiological studies carried out (which had identified a prevalence of about 4,1/100.000 individuals). It could be explained by increased awareness of symptomatology of disorders and improved diagnostic techniques and classification standards. Hence the indication to carry out a genetic panel that includes the most widely known genetic variants expressed in the general population in the diagnostic algorithm of autism. In addition, alongside the multitude and heterogeneity of genetic mutations involved, there are factors that could be defined epigenetic or otherwise related to the environment. For example, the use of iatrogenic drugs during the



gestational period, such as sodium valproate, commonly taken in the treatment of epilepsy, is related to a relative risk of developing autism of about 8 times greater in the new-child. This work aims to search for possible links between clinical phenotypes and radiological anomalies that may be relevant and pathognomonic in the subsequent diagnosis of ASDs. The evidence of a relevant statistical correlation between these anomalies and the diagnosis of ASDs might be helpful to recognize earlier the clinical and radiological phenotypes implied in the development of the ASDs. Moreover, an early diagnosis might lead to a better approach to the management and treatment of the disorder, improving the quality of life of these patients.

III. EXISTING METHODOLOGY

Early diagnosis of autism spectrum disorder (ASD) is paramount for ensuring affected individuals receive timely interventions and support. In a recent paper, researchers utilized two distinct algorithms, namely the Random Forest Classifier and the Decision Tree Classifier, to analyse a dataset related to ASD. These machine learning algorithms are adept at identifying patterns and characteristics associated with ASD, making them valuable tools for classification tasks. The paper's findings have significant therapeutic implications, as they hold the potential to facilitate the early detection of ASD. By leveraging these algorithms to analyse relevant data such as behavioural assessments and genetic factors, clinicians can identify individuals at risk of ASD at an early stage. This early identification enables prompt access to support services, interventions, and treatments tailored to the individual's needs, ultimately improving outcomes and enhancing the quality of life for individuals with ASD and their families. Random forests can also be employed to predict various outcomes associated with ASD, such as the effectiveness of different intervention strategies, the likelihood of co-occurring conditions, or the long-term prognosis for individuals with ASD. By analyzing patterns in the data, the classifier can provide valuable insights into potential trajectories and outcomes for individuals on the autism spectrum. Overall, the integration of machine learning techniques in ASD diagnosis offers promise for optimizing resource allocation, reducing diagnostic delays, and improving long-term prognosis.

IV. PROPOSED METHODOLOGY

Brain-based measures may facilitate early detection of ASD by identifying neurobiological differences in infants and young children at risk for ASD. Early intervention is critical for improving outcomes in individuals with ASD, making early detection essential. Studying the brain in individuals with ASD provides valuable insights into the neurobiological mechanisms underlying the condition. This knowledge can inform the development of targeted interventions and treatments tailored to the specific neurobiological profile of individuals with ASD. CNNs are commonly used for analysing image data, making them well-suited for tasks such as facial expression recognition or analysing brain imaging scans (e.g., MRI or fMRI) to identify structural or functional differences associated with ASD. The proposed system aims to develop a real-time framework for classifying facial expressions in streaming video to detect potential indicators of autism spectrum disorder (ASD). In this system, facial features will be extracted using the Grassmann algorithm, a technique suitable for high-dimensional data analysis such as images or video frames. These features will then be used to classify facial expressions, determining whether they display characteristics associated with ASD. To accomplish this, machine learning algorithms like Convolutional Neural Networks (CNNs) will be employed to build models trained on datasets of facial expressions from individuals with and without ASD. These models will be trained to identify patterns indicative of ASD, enabling accurate classification of facial expressions in real time. Users will have the option to input their own facial images or video frames for classification, and the system will provide feedback on whether the expressions exhibit features consistent with ASD. Overall, this approach offers a novel method for early ASD detection through real-time facial expression analysis, potentially enabling timely intervention and support for individuals on the autism spectrum.

V. GRASSMANN ALGORITHM

For each frame in a video sequence, we first detect and crop the face regions. We then partition all the cropped face images into K different partitions. We partition the cropped faces by a Grassman algorithm type of algorithm that is inspired by video face matching algorithm. Sampling and characterizing a registration manifold are the key step in our



proposed approach. The proposed algorithm presents a novel perspective towards frame selection by utilizing feature richness as the criteria. It is our assertion that quantifying the feature richness of an image helps in extracting the frames that have higher possibility of containing discriminatory features. In order to compute feature-richness, first the input (detected face) image I is pre-processed to a standard size and converted to grayscale. By performing face detection first and considering only the facial region, we ensure that other non-face content of the frame does not interfere with the proposed algorithm. Given a pair of face coordinates, we determine a set of affine parameters for geometric normalization. The affine transformation maps the (x, y) coordinate from a source image to the (u, v) coordinate of a normalized image.

Input: A set of P points on manifold

$\{X_i\}_P \in G(d, D)$

Output: Karcher mean μ_K

1. Set an initial estimate of Karcher mean $\mu_K = X_i$ by randomly picking one point in $\{X_i\}_P$

2. Compute the average tangent vector

$A = \frac{1}{P} \sum_{i=1}^P \log(X_i)$

$P \leftarrow P - 1$

$\mu_K \leftarrow \mu_K + A$

3. If $\|A\| < \epsilon$ then return μ_K stop, else go to Step 4

4. Move μ_K in average tangent direction $\mu_K = \exp_{\mu_K}(\alpha A)$, where $\alpha > 0$ is a parameter of step size. Go to Step 2, until μ_K meets the termination conditions (reaching the max iterations, or other convergence conditions).

VI. CONVOLUTIONAL NEURAL NETWORK ALGORITHM

A convolutional neural network is a feed-forward network with the ability of extracting topological properties from the input image. It extracts features from the raw image and then a classifier classifies extracted features. CNNs are invariance to distortions and simple geometric transformations like translation, scaling, rotation and squeezing. Convolutional Neural Networks combine three architectural ideas to ensure some degree of shift, scale, and distortion invariance: local receptive fields, shared weights, and spatial or temporal sub-sampling. The network is usually trained like a standard neural network by back propagation. A convolutional layer is used to extract features from local receptive fields in the preceding layer. In a network with a 5×5 convolution kernel each unit has 25 inputs connected to a 5×5 area in the previous layer, which is the local receptive field. A trainable weight is assigned to each connection, but all units of one feature map share the same weights. This feature which allows reducing the number of trainable parameters is called weight sharing technique and is applied in all CNN layer. With local receptive fields, elementary visual features including edges can be extracted by neurons. To extract the same visual feature, neurons at different locations can share the same connection structure with the same weights. The output of such a set of neurons is a feature map. This operation is the same as a convolution of the input image with a small size kernel. Multiple feature maps can be applied to extract multiple visual features across the image. Subsampling is used to reduce the resolution of the feature map, and hence reduce the sensitivity of the output to shifts and distortions. In our proposed CNN structure, multiple features can be extracted from each original eye data, and each feature has $n3$ dimensions.

Constructing the CNN Model

function INITCNNMODEL (θ , $[n1-5]$)

layerType = [convolution, max-pooling, fully-connected, fully-connected]; layerActivation = [tanh(), max(), tanh(), softmax()]

model = new Model(); for $i=1$ to 4 do

layer = new Layer(); layer.type = layerType[i]; layer.inputSize = n_i

layer.neurons = new Neuron [n_{i+1}]; layer.params = θ_i ; model.addLayer(layer);

end for, return model; end function



Training the CNN Model

Initialize learning rate α , number of max iteration $ITER_{max}$, min error ERR_{min} , training batches $BATCHES$ training, batch size $SIZE_{batch}$, and so on;

Compute n_2, n_3, n_4, k_1, k_2 , according to n_1 and n_5 ; Generate random weights θ of the CNN;

$cnnModel = InitCNNModel(\theta, [n_1-5])$; $iter = 0$; $err = +inf$;

while $err > ERR_{min}$ and $iter < ITER_{max}$ do $err = 0$;

for $batch = 1$ to $BATCHES_{training}$ do

$[\nabla J(\theta), J(\theta)] = cnnModel.train(TrainingDats, TrainingLabels)$, as (4) and (8); Update θ using (7); $err = err + mean(J(\theta))$;

end for $err = err / BATCHES_{training}$; $iter++$;

end while, Save parameters θ of the CNN

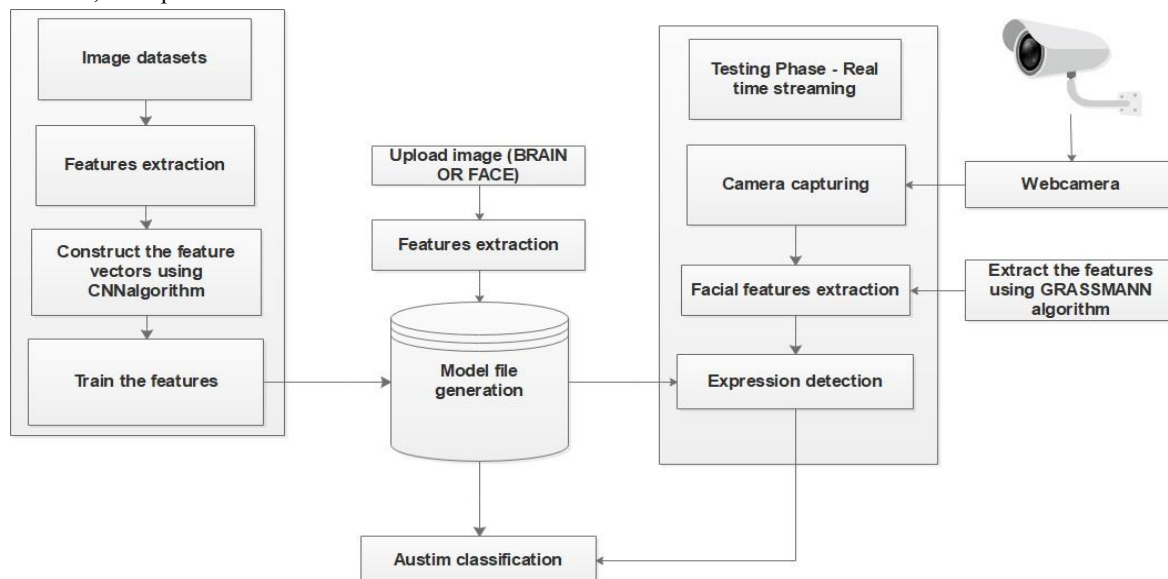


Fig 1: Proposed architecture diagram

VII. EXPERIMENTAL RESULTS

In this study, we can analyze classifiers in autism disorder detection datasets that are mutually from KAGGLE web spring. Table 1

S.NO	Attributes	Specifications
1	Objective	To detect potential indicators of autism spectrum disorder (ASD) through real-time facial expression classification.
2	Input	Streaming video frames or uploaded facial images.
3	Data Type	Image/Video (Facial expressions)
4	Target Users	Clinicians, therapists, parents, researchers in early ASD detection.
5	Algorithms Used	Grassmann Manifold Feature Extraction - CNN for classification
6	Model Training	Supervised learning on labeled data using CNN
7	Performance Metrics	Accuracy, Precision, Recall, F1-Score, Real-time latency

And appraise the presentation of the examination using following metrics

True positive (TP): the sensing systems produce a positive judgment for the model, and the text is present in the sample.



False positive (FP): the detection system produces a convincing outcome for the sample regardless of the fact that the sample does not contain the text.

True negative (TN): the detection methods generate a positive test result for the sample notwithstanding the fact that the sample does not contain the text.

False negative (FN): the detection methods generate a positive test result for the sample despite the fact that the sample contains text.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \quad (1)$$

That FP is equal to zero. As FP increases, the precision value decreases while the denominator value increase resultant in the opposite of what we want.

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}) \quad (2)$$

A good classifier should have a strike a chord of one (high). Only if the denominator and numerator are the same, as in $\text{TP} = \text{TP} + \text{FN}$, does recollect equal one, imply that FN is zero. As FN increase, the recall value decrease (which is undesirable) as well as the low widespread value increases.

As a result, the ideal exactitude and recall for a talented cataloguing model are one; imply that FP and FN are also zero. As a result, we want a value that take precision and recall into account. The F1-score, a estimate that takes precision and recall into account:

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Table 1: Accuracy comparison table

ALGORITHM	ACCURACY
Naives Bayes	70%
Support vector machine	80%
CNN	90%

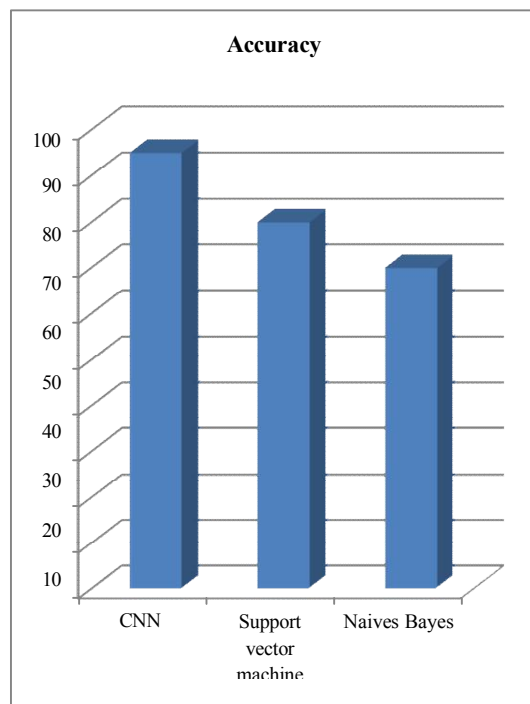


Fig 2: Performance chart



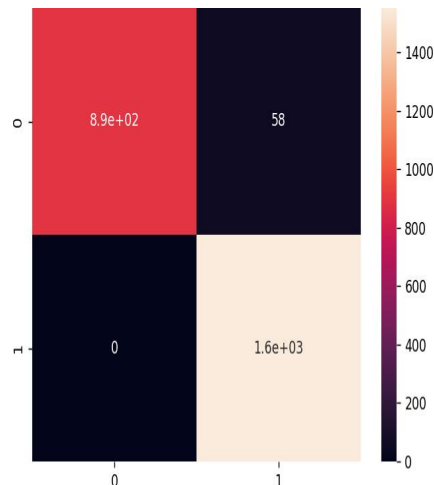


Fig 3: Confusion matrix Brain model

VIII. CONCLUSION

In conclusion, the development and implementation of deep learning-based approaches for autism detection represent a promising avenue for improving early diagnosis and intervention for individuals on the autism spectrum. By leveraging advanced neural network architectures, such as Convolutional Neural Networks (CNNs), Grassmann algorithm and clinicians can extract meaningful patterns and features from diverse datasets, including neuroimaging scans, face data and real time data. These deep learning models offer several key advantages, including improved accuracy in detecting subtle indicators of autism, enhanced scalability to handle large and complex datasets, and the potential for personalized treatment approaches tailored to individual needs. By applying CNNs to analyse facial images, researchers can potentially develop accurate and efficient tools for early ASD detection. This approach offers several advantages, including non-invasive data collection, scalability, and the ability to analyse subtle facial cues associated with ASD

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