A Dataset of Eye Movements for the Children with Autism Spectrum Disorder

Huiyu Duan
Shanghai Jiao Tong University
huiyuduan@sjtu.edu.cn

Guangtao Zhai
Shanghai Jiao Tong University
zhaiguangtao@sjtu.edu.cn

Xiongkuo Min
Shanghai Jiao Tong University
minxiongkuo@sjtu.edu.cn

Zhaohui Che
Shanghai Jiao Tong University
chezhaohui@sjtu.edu.cn

Yi Fang
Shanghai Jiao Tong University
yifang@sjtu.edu.cn

Xiaokang Yang
Shanghai Jiao Tong University
xkyang@sjtu.edu.cn

Jesús Gutiérrez
University of Nantes
jesus.gutierrez@univ-nantes.fr

Patrick Le Callet
University of Nantes
patrick.le-callet@univ-nantes.fr

ABSTRACT

Social difficulties are the hallmark features of Autism Spectrum Disorder (ASD) and can lead to atypical visual attention towards stimuli. Eye movements encode rich information about attention and psychological factors of an individual, which could help to characterize the traits of ASD. Learning atypical eye movements of the individuals with ASD towards various stimuli is important and has many application scenarios. However, due to the lack of open datasets, research in this sense is still limited. In this work, we present an open dataset of eye movements of children with Autism Spectrum Disorder. It consists of 300 natural scene images and the corresponding eye movement data collected from 14 children with ASD and 14 healthy controls. In particular, fixation maps and scanpaths are available in the dataset. Based on this dataset, researchers could analyze the visual traits of children with ASD and design specialized visual attention models to promote research in related fields, as well as design specialized models to identify the individuals with ASD. The dataset can be accessed in *http://doi.org/10.5281/zenodo.2647418*

CCS CONCEPTS

• **Information systems** → **Multimedia databases**; • **Applied computing** → *Psychology*.

KEYWORDS

Eye movement, Autism Spectrum Disorder, dataset, visual attention, images

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1 INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder. Individuals with ASD usually show social communication impairments, as well as restricted and repetitive behaviors. Atypical sensory perception is identified to be the core characteristic of autism [13]. In this sense, visual attention is an important aspect of sensory perception, so individuals with ASD often show atypical visual attention to various visual stimuli [17]. In particular, eye movements encode a wealth of information about attention, oculomotor control and personal psychological factors. Also, gaze features related to saccades and fixations have demonstrated their usefulness in the identification of mental states, cognitive processes and neuropathologies [7, 18], notably for people with ASD. Thus, from eye movements of people with autism, it is possible to characterize ASD traits and even help with ASD diagnosis.

Although some studies have been already carried out on the topic, they mainly used stimuli with restricted contents (e.g., only faces), and, as far as we know, there is little open dataset which collected the eye movement data from children with ASD. In this sense, the availability of public datasets is crucial to support the research on visual attention [4, 9, 12], and they are essential to progress on: 1) the development specialized models (saliency prediction or saccadic models) that fit gaze behavior of people with ASD, and 2) diagnosis of ASD individuals. Firstly, visual attention models of ASD have great significance to related research field, since with the help of these models, researchers could characterize the visual attention traits of ASD, better understand ASD, and even design specific materials (e.g., textbooks) for people with ASD [19]. Secondly, in relation with ASD diagnosis, researchers can propose models to classify the individuals with ASD and healthy controls from gaze data. Since the diagnostic procedure of ASD is expensive, subjective, and time-consuming, it can be of great value to use visual attention methods to assist the diagnosis of ASD.

In our previous work [6], we constructed an open dataset for the visual saliency prediction for children with ASD, but we did not

Table 1: Experiments settings and test conditions.

Category	Items	Details
Stimuli	Image number	300
Eye tracker	Model	Tobii T120
	Size	17 inch
	Resolution	1280 × 1024
	Sampling rate	120 Hz
	Tracking distance	65 cm
Subjects	ASD subjects number	14 reserved
		6 discarded
	TD subjects number	14 reserved
Experiment procedure	Viewing time	3s
	Gray interval	1s
	Presentation order	Random
	Session number	10
	Task condition	Free-viewing

provide any temporal information for further discussion. Therefore, in this paper, we construct a dataset of eye movements of children with ASD. It consists of 300 images and the corresponding eye-tracking data collected from 14 different children with ASD and 14 different healthy controls. It is worth noting that the corresponding eye movement data of healthy controls will also be released to facilitate research related to diagnosis. In particular, we provide sequence and duration information for each fixation point. This information could further help to compare and classify the visual patterns between children with ASD and healthy controls. The purpose of this dataset is to drive efforts of visual attention modelling community towards a healthcare societal challenge. The dataset is publicly accessible in *http://doi.org/10.5281/zenodo.2647418*.

The rest of paper is organized as follows. First, a brief overview of related works is presented in Section 2. Then, Section 3 describes the database and the details of the subjective experiment carried out to generate the database. Section 4 presents data analysis and some preliminary results based on the database. Finally, some conclusions are provided in Section 5.

2 RELATED WORK

Given the importance to characterize visual attention of people with ASD, many studies related to this topic have been conducted [17]. For instance, Osterling *et al.* [11] reported reduced joint-attention of individuals with ASD. Also, Chawarska *et al.* [2] showed that people with ASD have reduced attention to social scenes, and Sasson *et al.* [16] used competing social and object images to study the preference of the visual attention of individuals with ASD. In this sense, Wang *et al.* [20] studied the visual attention of individuals with ASD on multi-level features and indicated that they tend to pay more attention to low-level features of the stimuli (e.g., contrast, colour, and orientation).

Furthermore, some researchers analyzed eye movements to diagnose individuals with ASD. In particular, based on the gaze patterns of children with ASD in a face recognition task, Liu *et al.* [10] proposed a machine learning method to classify children with ASD and control groups. With the advent of deep neural networks (DNN),

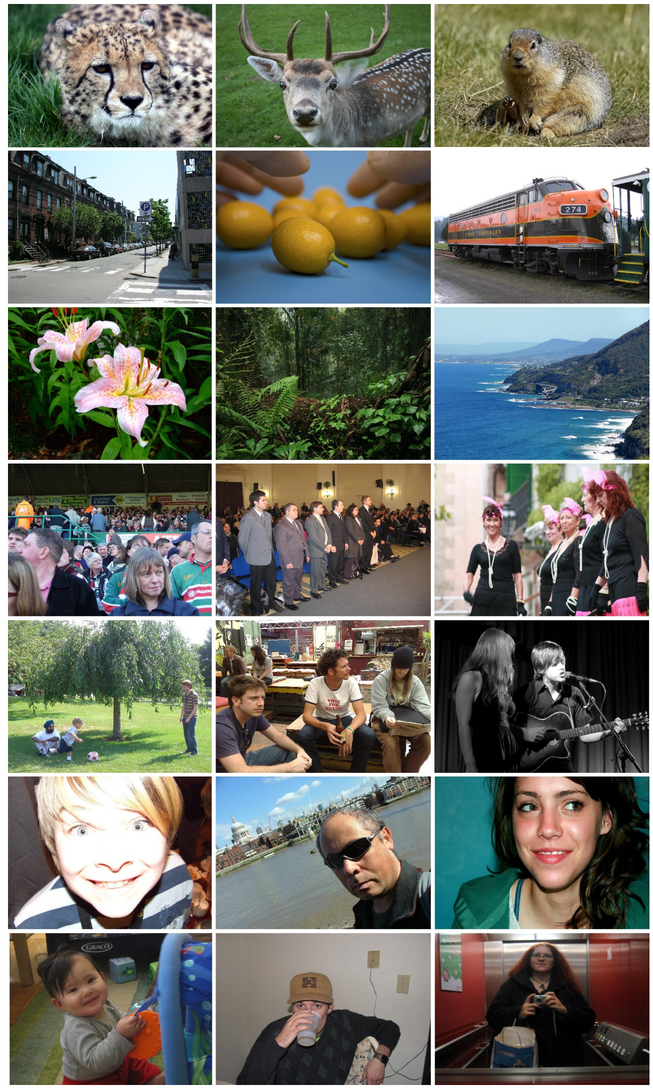

Figure 1: Three sample images from each of the seven classes used for the test. (Top Row): Animals, (Second Row): Buildings or objects, (Third Row): Natural scenes, (Fourth Row): Multiple people, (Fifth Row): Multiple people and objects, (Sixth Row): Single person, (Bottom Row): Single person and multiple objects.

Jiang *et al.* [8] used the fixation data of people with autism to fine-tune one saliency prediction algorithm and classified the individuals with autism and healthy controls with better accuracy. Also, Cheung *et al.* [3] studied the association of visual search abilities with later ASD diagnosis.

Also, we carried out some preliminary experiments to obtain visual attention models of ASD *et al.* [6]. In particular, we fine-tuned five state-of-the-art saliency prediction models based on a preliminary version of the presented dataset. In brief, compared to healthy controls, individuals with ASD were reported to have reduced attention to social and semantic stimuli (e.g., faces, conversations, etc.)

but focus more on non-social and low-level stimuli (e.g., vehicles, electronics, etc.) [5, 15]. Also, compared to raw saliency models, experimental results indicated that a relatively good visual attention model for ASD were obtained.

Finally, it is worth noting the organization of the Grand Challenge "Saliency4ASD: Visual attention modeling for Autism Spectrum Disorder" (at ICME 2019). The purpose of the Saliency4ASD Grand Challenge is to align the visual attention modeling community around the application of characterizing and diagnosing ASD, supporting the development of modelling and classification approaches, by providing a framework, datasets and tools. In particular, the Grand Challenge includes two tracks: 1) to develop models (saliency prediction or saccadic models) that fit gaze behavior of people with ASD, and 2) to propose models able to classify ASD and typically developed viewers using gaze data. The first goal can be particularly useful to develop ad-hoc materials and CHIs (Computer Human Interfaces) that are adapted for people with ASD, while the second goal, in addition to early stage detection of ASD, could be relevant to monitor the efficiency of any remediation protocol. The evolution and results from this effort will be reported in the website *https://saliency4asd.ls2n.fr/*, which would set a baseline for the research community in the topic.

3 DATASET DESCRIPTION AND SUBJECTIVE EXPERIMENT

3.1 Stimuli and Apparatus

To analyze the traits and the differences of the eye movements across children with ASD and healthy children under different visual stimuli, we collected 300 images from [9], which is a large public database that contains images with various scenes. The test stimuli include 40 images with various animals, 88 images with buildings or objects, 20 images with natural scenes, 36 images with multiple people in one image, 41 images containing multiple people and objects in one image, 32 images with single person in one image, and 43 images with single person and objects in one image. As an example, three images from each category can be seen in Figure 1. With the help of these various kinds of stimuli, our dataset could help researchers to better understand the traits of the visual attention of children with ASD.

We use Tobii T120 Eye Tracker to display the images and record the eye movements. This eye tracker has a 17 inches display with a resolution of 1280×1024 (width $\times$ height). The sampling rate of the eye tracker is set to 120 Hz, and the effective tracking range is from 50 to 80 cm. In our experiments, subjects are seated at a viewing distance of 65 cm approximately from the eye tracker.

3.2 Subjects

We recruited twenty high-functioning children with ASD who met DSM-V diagnostic criteria for autism [1]. However, due to lack of patience and attention, it is difficult to conduct the eye movement calibration procedure for children with ASD. Thus, among twenty participants with ASD, only fourteen subjects could complete the calibration step and obtain effective eye movement data. The remaining participants with ASD were 5 to 12 years old and the average age of the subjects was 8 years. In addition, fourteen healthy children were recruited as controls, whose age also ranged from 5 to 12 years old. The average age of healthy controls was 8 years. We also matched the gender, race, education, etc. of the two groups to ensure the generalization of the database. All participants had normal or correct-to-normal visual acuity. Before the experiments, the parents of all participants gave written informed consent.

3.3 Experimental Procedure

We shuffled 300 images into a random sequence. It is difficult for individuals with ASD to concentrate on the screen, so we split the experiment into ten recording sessions with 30 images in each session. During each session, test stimuli were also shuffled into a random order. Each image was presented at its full resolution for 3 seconds and followed by a one-second gray screen mask. We performed the eye tracking calibration procedure before each session for every participant to guarantee the reliability of the data. Before the experiment, all subjects were told to look at stimuli freely. Due to the difficulty in concentrating on the screen, during the experiment, we need to remind the children with ASD occasionally to look at the screen. The same experimental procedures were also performed for healthy controls. Table 1 list the detailed experiments settings and test conditions.

4 ANALYSIS AND RESULTS

4.1 Stimuli Analysis

The eye movements data of the children with ASD and healthy children were collected when various image stimuli were presented. As described in Section 3.1, test stimuli contain 7 categories. To facilitate other researchers to analyze the eye movements traits based on our database, we annotated semantic level features of 10 categories, including faces, people, background people, crowd, texts, hand-touched objects, animals, plants, buildings, and objects. Figure 2 shows the sample annotations for 10 categories. The detailed number of each category is listed in Table 2. The annotation file is available and will be released with this dataset.

4.2 Visual Attention Analysis

Fixation maps are generated from the eye movement data collected in the experiment. We overlay all fixation points of the children with ASD in a binary map, in which the positions of fixation points are set to 1 while other positions are set to 0, obtaining the fixation map of the ASD participants. With the same method, we get the fixation map of the healthy controls. Then we smooth the fixation maps with a Gaussian kernel to generate the fixation density map (FDM, also called visual attention map). The standard deviation of the Gaussian kernel is usually set to 1 degree of the visual angle. In this dataset, we set the standard deviation of the Gaussian kernel as $\sigma = 40$. By comparing the visual attention map between the children with ASD and healthy controls, many similarities and differences are observed, which can facilitate further research in related fields. Figure 3 shows some sample images and their corresponding visual attention heat maps from ASD subjects and healthy controls. In each subfigure of Figure 3, the three columns from the left to the right represent the raw image, the heat map of the children with ASD, and the heat map of the healthy controls.

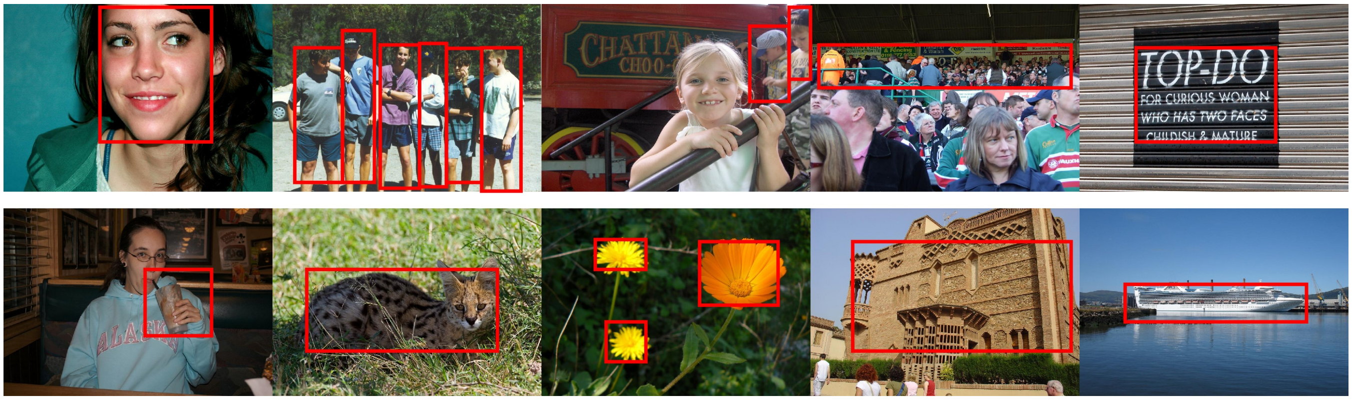

Figure 2: Example annotations of 10 categories.

Table 2: Experiments settings and test conditions.

Category	faces	people	background people	crowd	texts	Handheld objects	animals	plants	buildings	objects
Number	22	245	14	34	27	55	70	29	53	173

Specifically, on one side, Figure 3 (a)-(d) shows the visual attention heat maps of ASD subjects and healthy controls when the stimuli are animals, plants, natural scenes, and buildings or objects. As shown in Figure 3 (a), it is obvious that the two visual attention maps from the children with ASD and the healthy controls are similar when animals are the main contents of the image. Figure 3 (b) shows the visual attention comparison when stimuli are plants. For object-level features, ASD participants have similar preference to the healthy controls. However, for low-level features, they have different visual preferences to some extent. In Figure 3 (c), for natural scenes, a new phenomenon against the center bias described in [19] is observed. In natural scenes, while an obvious center bias can be observed in the visual attention maps of healthy controls, children with ASD fixated more on pixel-level features and the distribution of their fixation points is very scattered. Finally, Figure 3 (d) shows samples of buildings and objects, where it is evident that individuals with ASD have similar preferences for object level features but different preferences for semantic features.

On the other side, Figure 3 (e)-(i) show the visual attention heat maps of ASD subjects and healthy controls when the stimuli are people-induced and illustrate the atypical visual preference of the individuals with ASD. Comparing the visual attention heat maps of ASD subjects and healthy controls in Figure 3 (e), ASD subjects have significant object or animal preferences under these stimuli. Figure 3 (f) shows multiple people scenarios. Individuals with ASD will concentrate more on the people or interesting objects in the center zone compared with the healthy controls. Regarding the effect of human faces, we show three images in Figure 3 (g). It is obvious that different face emotions or expressions have different impacts on the visual attention of children with ASD and healthy controls. Also, Figure 3 (h) shows the hand bias [6]. Children with ASD will pay more attention to the hands or the objects in their hands, especially when there is interaction between objects and the hand or when there is a significant action on the hand. Finally, Figure 3 (i) shows another different bias named as background bias. Children with ASD will pay more attention to the people or objects in the background than healthy controls.

Apart from these comparisons between the heat maps of children with ASD and healthy controls, there are many other atypical or typical traits of the visual attention of children with ASD that can be explored by researchers with the materials included this dataset.

4.3 Scanning strategies

As illustrated in [14], for the individuals with ASD, “more sever disability leads to more atypical scan patterns". Thus, studying the differences and similarities of the scanpaths is important for the definition of visual attention traits of ASD individuals. In this sense, it is also important to analyze eye movements data to identify the ASD [21]. However, previous researchers usually explore the similarities and differences of scanpaths on human faces. Thus, in this dataset, we also provide the data of the fixation sequences to analyze the scanning strategies. To visualize the evolution of exploration patterns, Figure 4 shows the heat maps of images with seven categories by a second-by-second visualization. The first column represents the raw images. The second to the fourth columns represent the visual attention heat maps of the children with ASD in the 1st, 2nd, 3rd second, respectively. The fifth column represent the visual attention heat maps of the children with ASD in all three seconds. The sixth to the eighth columns represent the visual attention heat maps of healthy controls in the 1st, 2nd, 3rd second, respectively. The ninth column represent the visual attention heat maps of healthy controls in all three seconds. Similarities and differences can be observed from this figure, which can be further studied with a deeper analysis of the provided dataset.

5 CONCLUSION

This paper presents a open dataset of eye movements for children with Autism Spectrum Disorder, including 300 images with various

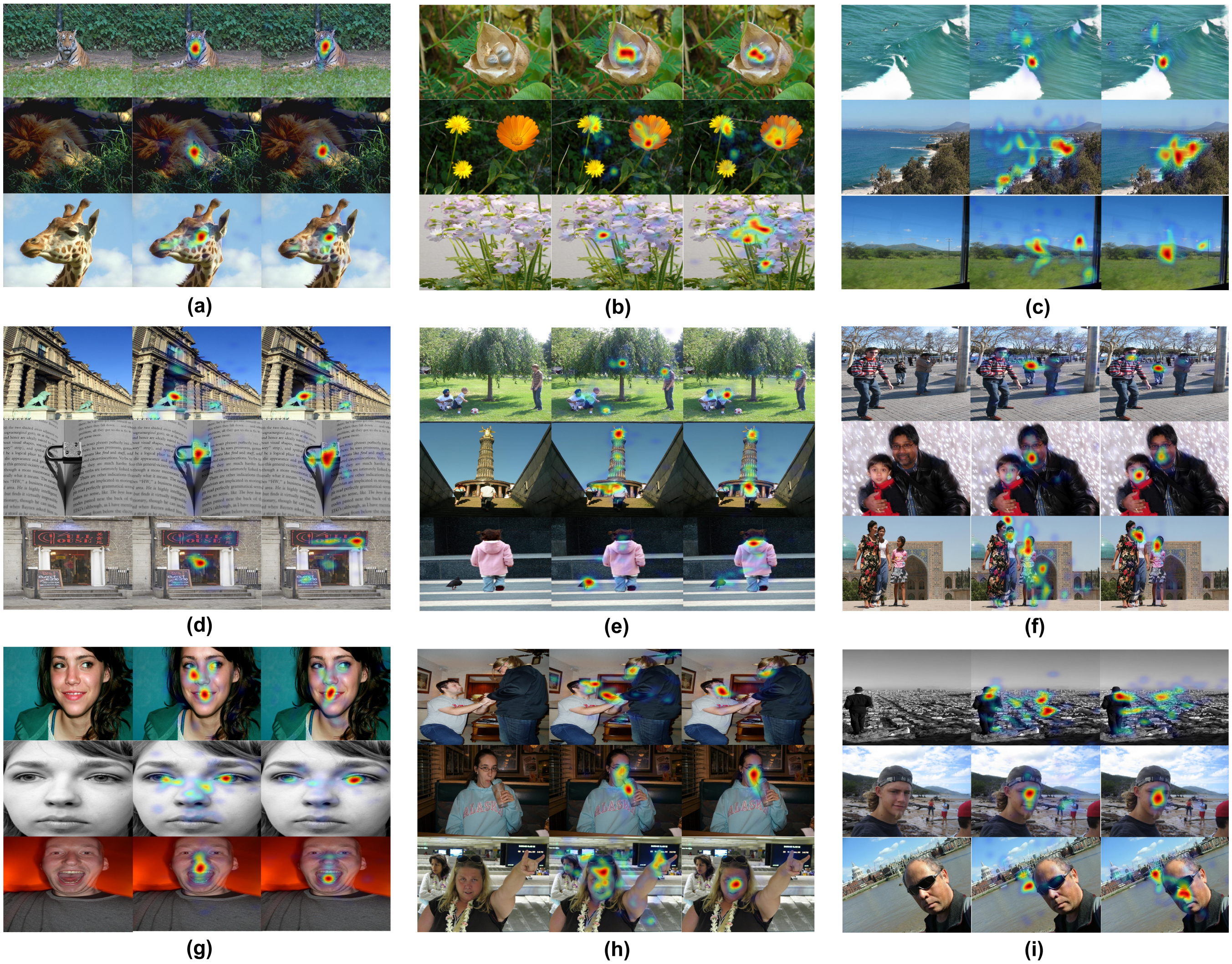

Figure 3: Comparison between the saliency maps of children with ASD and healthy controls. In each subfigure, the three columns (from left to right) are: the raw image, the heat map of children with ASD, and the heat map of healthy controls. Each subfigure correspond to one category: (a) animals (b) plants (c) natural scenes (d) buildings or objects (e) objects bias (f) center bias (g) attention on faces (h) hand bias (i) background bias.

scenes and the corresponding eye-tracking data collected from 14 children with ASD and 14 healthy controls. We conducted subjective experiments to collect eye movement data, in which test images were displayed in a random order at full resolution during 3 seconds. We have annotated semantic level features of 10 categories to facilitate other researchers analyze the eye movements traits of the children with ASD based on our database. The dataset contains the images, annotation files, fixation and saliency maps, and scanpaths, together with parsing tools. The dataset, which is used in the Saliency4ASD Grand Challenge (*https://saliency4asd.ls2n.fr/*), is publicly available (*http://doi.org/10.5281/zenodo.2647418*) with the objective of helping the research community to develop visual attention models that characterize ASD individuals and classification techniques to help on diagnosis of ASD.

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Figure 4: Heat maps of images with seven categories by a second-by-second visualization. First column: raw images, Second to Fifth column: heat map of the children with ASD, Sixth to Ninth column: heat of the healthy children.

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