JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 1, 2022, p. 286-297
https://publishoa.com
ISSN: 1309-3452

Review of Autistic Detection Using Eye Tracking and Vocalization Based on Deep Learning

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Received 2022 March 15; **Revised** 2022 April 20; **Accepted** 2022 May 10.

Abstract
Autism is a neuro developmental disorder usually diagnosed in childhood. Autism is identified by repetitive and restricted behaviors, and conflicts in communication. Eye tracking has long been used to research the development of ASD autism spectrum disorder as a technique, as it is a tool that tracks visual activity and tells us information such as where and for how long something is stared at by a person. Eye tracking gives a very immediate and interpretable indicator of an individual's attention, which is something that no other biomarker... will do. Effectively, in real-time, you get to know where a person allocates their attention, which tells you all about mental processing. Eye tracking is now a highly regarded method in ASD research as it enables the precise tracking of the gaze of an individual. This knowledge offers empirical insight, as a proxy for cogn. So speech-language characteristics of vocalizations and face recognition are the required features . Exam pre-linguistic vocalizations for a period of time using some smart devices. Diagnosing Autistic may be challenging to diagnose since there are presently no advanced diagnostic techniques available; instead, clinicians must assess the child's behavior and development to determine a diagnosis. In addition, to correctly evaluate a youngster, repeated exams are usually required. The issue is that the analysis of vocalization specificities, newborn vocalization analysis, and the analysis of certain descriptors facial characteristics picked in various situations and for children are all problematic.The aim of this proposal is a perfect autistic detection using a classification approaches achieve with high accuracy and for subject-wise identification in a subject-independent 3-fold cross-validation scheme. At the neural level, neural activation patterns and neural adaptation to faces in face-related brain regions. In terms of functional connectivity, So amygdale seems to be more strongly connected to inferior occipital cortex and V1 in individuals with ASD. Overall, the findings indicate that neural representations of facial identity(eye movement abnormal) and expression have a similar quality in individuals with and without ASD, but some regions containing these representations are connected differently in the extended face processing network.In this research, we presented a review and presentation of the latest research that specialized in detecting autism using eye tracking and vocalization technology, both separately.Because of the two methods of high accuracy in detecting autism, both what if they were used together. The expectable results may be an important contribution to facilitate earlier identification of autistic disease .
Keywords: Autism Spectrum Disorder (ASD); Eye Tracking ; vocalization ;Deep learning ,neural network .

Introduction

In recent years, however, eye-tracking and sensing technologies, which have become the most powerful tools for detecting autism spectrum disorder (ASD), have emerged as the most extensively used techniques of diagnosing the illness. When compared to children with regular development, children with ASD do not make eye contact during social interactions, according to a number of studies [1]. As a result, the use of eye-tracking technology may be beneficial in the evaluation of eye movements that are difficult to detect with the naked eye (e.g. saccades and smooth pursuit). The technique for detecting vocalizations was also used, which allowed researchers to identify the children who were engaging in abnormal behavior. The diagnosis of autism spectrum disorder (ASD) is very difficult since it requires a lengthy time of observation of the behavior of children with ASD. With an estimated frequency of one in every 88 people, autism spectrum disorder (ASD) is a cause for worry for families and governments who are concerned about how to diagnose ASD in children at an early stage of their lives [2]. Following the findings of this research, the use of eye-tracking and a range of other technologies to detect autism in children at an early age is being explored. According to previous studies, the majority of eye-tracking and sensing technologies researchers have focused on analyzing differences in social attention and behavior among samples of children with Autism Spectrum Disorder (ASD). The purpose of research into autism spectrum disorders is to aid autistic experts in establishing an accurate diagnosis of ASD in children and adolescents during their formative years. According to the findings of the research, 80 percent of children with autism who were diagnosed at an early stage were able to increase their level of communication [2] if they received early intervention. As an alternative to observing eye movement for a limited length of time to diagnose autism spectrum disorder [ASD], psychologists may use an eye tracking strategy to investigate the eye fixation associated with ASD [3,4]. There are many different types of sensors that may be used to identify abnormal behaviors that might assist in the appropriate diagnosis of autism spectrum disorder. Here are a few examples. In this assessment of previous research, which is based on two technologies for researching autistic children, autistic children between the years of 2013 and the time of publication of this study were examined. Eye-tracking technology and vocalizing technology are two examples of such technologies.. Certain researchers additionally use a variety of technologies and methodologies, such as questionnaires and developmental evaluations, EGG and MRI scans, as well as video-based screening and diagnostic processes, among others. RELATED WORK

A. Eye-Tracking Technology

The majority of the research included in this review employed eye-tracking equipment to gather data on children's eye fixation and eye motion while they were observing visual stimuli in order to diagnose autism by comparing children with ASD and children with TD. The experiment room should be dark and soundproof to provide the best results. The kid is sitting on his or her parent's lap in front of the screen, where he or she will be exposed to visual stimuli. There are two sorts of visual stimuli: dynamic visual stimuli and static visual stimuli, and the child will be exposed to both. The researchers employed Tobii eye-tracking devices to capture the children's eye movements in order to utilise the data in later procedures.

According to Almourad et al.[4], eye tracking technology was used to compare and study the gaze patterns of autistic children and normally developing youngsters in order to better understand their behavior. The information was gathered from 65 individuals, including 34 children with ASD and 31 children with TD. The average age of the participants was 8 years old. The data was gathered using the Tobi X2 eye tracking system. During the experiment, the children sat in front of the eye tracker device and fixed their gaze on several items (including a tomato, football, banana, tomato, and a human child's), with the scientist recording their eye fixation. The researchers discovered that children with autism had less concentration on their eyes and indicated interest in gazing at the lips than typically developing youngsters in this study.

Wan, G., et al. [5] The researchers [presented an approach for detecting autism in its early stages. The children in the research varied in age from 4 to 6 years old, and they comprised 37 children with autism and 37 children who were developing normally. They were divided into two groups. The data on the experimental stimuli was collected using a portable Eye Tracking equipment from SMI called the RED250. The children were shown a 10-second silent video clip of an Asian female speaking, which was played in the background while the video clip was being displayed. They were as follows: backdrop; body (shoulders, neck, chest, and hair); outer-face (the area of the face excluding the mouth, nose, and eyes); person (body, hair, and face); face (outer-face); eyes; nose and mouth; nose and mouth; nose and mouth; nose, mouth, and eyes; nose, mouth and eyes; nose, mouth and eyes; nose, mouth and eyes; nose, mouth and eyes; nose, mouth and eyes; nose, mouth and eyes; nose, The classification accuracy was 85.1 percent, the sensitivity was 86.5 percent, and the specificity was 83.8 percent, according to the results.

Del Bianco, T., et al. [6] explored the ASD's interaction with autistic people' faces and eyes. The research included 20 people with ASD and 20 people with TD, and used an eye-tracker (T120). The stimuli used were 24 10-second movies, and participants may answer questions after seeing the films using the keyboard as instructed. For example, pupils were asked to identify an item on the model's body and answer the question "Who got the pen?" Participants pushed A if the model was in the middle, L if the model was to the left, and R if the model was to the right (to the right). Focus on AOIs, faces, bodies of models (backdrop), and center model (center model). Children with autism spectrum disorders (ASD) have diminished facial focus.

Pierce, K., et al. [7] Children with autism spectrum disorders (ASD) in their early phases of development may be identified using theorized eye-tracking patterns. There were 334 youngsters from six distinct groups that took part in the study (115 children with ASD, 20 children with ASD-Features, 57 children with DD, 53 children with other disabilities, 64 children with TD, and 25 children with SIB). Using a Tobii T120 eye-tracker equipment, the researchers were able to collect their data. An animated movie was presented to the children, which was made up of AOIs that were made up of DGI and DSI images that were placed side-by-side and in which different scenes changed at the same time was shown to them. Specifically, the findings showed that the ASD sensitivity was 21%, the specificity was 98 percent, and the positive predictive value was 86 percent. It is important to note how children with autism spectrum disorder and typically developing youngsters interact when they react to and begin joint attention exercises., L. Billeci and colleagues [8] It was

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Volume 13, No. 1, 2022, p. 286-297
https://publishoa.com
ISSN: 1309-3452
discovered that there were differences in the visual patterns of the two groups. Youngsters with autism spectrum disorders (ASD) were included in the study alongside children who were developing normally (TD). In this work, the SMI Eye Tracker device was used to collect data. It was determined by the researchers in their study that children with autism exhibited visual patterns that were different from the patterns seen in children who were growing normally.
T. Falck-Ytter and colleagues [9] Specifically, they looked at how autistic children interacted with other kids. The research included 39 participants with ASD and 28 persons with TD who were all diagnosed with the disorder. Prior to conducting the experiment, the investigator showed the participants a short video clip of two young toddlers playing with a toy while employing nonverbal communication in front of the TD and ASD children. The eye-tracking data was collected with the use of a Tobii T120 gadget. It received an amazing accuracy rating of 0.91 for its category.
M. K. Kwon and colleagues [10] studied the degrees of fixation in the eye-region fixation in 385 toddlers ranging in age from one to forty-seven months (143 with ASD and 242 TD). An eye-tracking device, the Tobii T120, was used to capture the participants' eye movements. The youngster sat on his parent's knee, which served as a cushion, and watched a 43-second video of the lady utilizing hand gestures to emphasize several well-known words. The researchers used statistical analysis as part of experiment 1,2 in order to count the number of fixations in each portion of the video, such as the beginning and finish (eyes, face, nose, mouth, body, background). According to the results of the research, women with ASD exhibited a stronger fixation with the lower part of their bodies than males (mouth, body)
The data from 14 autistic children and 14 normally developing youngsters was gathered by Duan, H., et al.[11]who was in charge of recording the children's eye movements According to this research, the 300 images were separated into 10 sessions with each session showing 30 shots (animals and buildings, objects and natural settings, among other things). After each picture was presented on the screen for three seconds, there was a one-second gray screen, followed by another image and so on. Using an eye tracking device such as the Tobii T120 was agreed upon as a solution. The researchers did an examination of the data acquired from the fixation site they placed 1 in when the map was visible; otherwise, they set 0. This was done in both ASD and TD. ASDs have greater fixation on their hands and objects, whereas TDs have more fixation on their faces, according to the results of this research.
Seepold, R., et al.[12] constructed a model to examine the differences between children with autism and children who are ordinarily developed. It was discovered in 20 children with autism spectrum disorder (ASD) and 19 children with Tourette's syndrome. Each of the youngsters was shown a total of 700 photographs, which comprised the dataset. In one second, each image is revealed. In order to evaluate the eye-tracking data, SVM classification was employed on the basis of a three-layered architecture, which included pixel-level object level, semantic-level feature, and the center of the image and the background. The researchers discovered that those with ASD are more likely than those with TD to pay attention to the center of a picture. As a result of the classification, a level of accuracy of 0.936 is attained.
M. Lee and colleagues[13] sought to examine whether there are any common tendencies among parents that could have an influence on the skills of their children. By using eye-tracking, they were able to assess storytelling skills in children with autism spectrum disorders and their parents based on variations in structure and emotional content. Participants from children included 37 individuals with autism spectrum disorder (ASD) and 38 individuals with TD who did not have a family history of ASD. Participants from parents included 151 individuals who had a family history of autism spectrum disorder and 63 parents who did not have a family history of autism spectrum disorder. It was decided that the AOIs would be the face and body areas depicted in each photograph, with the eye movement being recorded using an eye tracker from the Tobii T60 series. They carried out an analysis of the data by calculating the fixation data in each AOI and then comparing the results. Genetic factors that affect linguistic abilities, according to the findings, may have an impact on autism spectrum disorder.
Sabatos-DeVito et al.[14] When comparing children with ASD to their DD and TD peers, it was discovered that they had disengaged and oriented attention. ASD = 19, TD = 20, and DD = 11 were the ages of the subjects, who ranged from 4 to 13 years old. The Tobii x 120 Eye-Tracker was utilized to capture the eye movements of the subjects throughout the study. They also put a web camera to capture the expressions on people's faces and the patterns of their gaze. A non-social object with visually and acoustically attractive characteristics served as the stimulus in this experiment. The stimuli were displayed to the youngster when he was seated on his parent's lap at a distance of 60 cm from the Tobii TX300 eye tracker device, and the researcher provided the stimulus to him while he was sitting on his parents lap. Eye-tracking data was retrieved and converted to CSV format so that the number of fixations on the screen's x/y axis could be counted and examined. Specifically, they observed that ASD groups were much slower to disengage as a consequence of the dynamic stimuli, as opposed to the static stimuli, and that this was true across the board.
G. A. Alvares and colleagues [15] It was discovered that they had successfully developed and tested a novel approach for drawing the attention of autistic youngsters to faces, and that it was effective. The people in the study varied in age from 5 to 12 years old and were diagnosed with autism spectrum disorder (ASD) (ASD). For the eye-tracking exercises, both social and non-social photographs are employed, and a game called "Frankie and Friends" is used to direct the attention of the autistic children to faces in their surroundings. According to the results, after receiving instruction, the kids in the training group significantly increased the percentage of engagements to faces when compared to objects in comparison to other items.

According to G., Bölte, S., et al. [16], the combined attention of autistic children was tested by following gaze and head direction. A total of 64 10-month-old children took part in the study; 46 had been identified with ASD and were at high risk, whereas 17 had been diagnosed with ASD and were at low risk. Tracking the subject's gaze was made possible with the TobiiTX300 device. While a researcher examined different items in the room, the volunteers stood about and watched. It was determined if the subject's performance was better when he moved his eyes and head to the items, as opposed to when he only moved his eyes. The findings from the high-risk ASD group revealed eye and head movement following the gaze, whereas the results from the low-risk ASD group showed just eye movement.

A study by E. Bataineh et al. [17] TD and ASD children exposed to social interaction stimuli were studied using eye-tracking analysis to see what kinds of visual patterns and behaviors they displayed. The Tobi X2 model was used to collect eye-tracking data from 65 youngsters, 34 of whom had ASD and 31 of whom had TD. Images of bananas, faces, tomatoes, and footballs were used to test the children's ability to follow their own eyes in the research. In comparison to children with autism spectrum disorders (ASD), TD children's gaze were shown to be more fixated on the face.

KB, P. R., et al.[18] created an Using virtual reality, a social communication platform that is eyegaze-aware Goal: To show how well an autistic child's social communication abilities measure up. They built a virtual birthday party, among other things, using a VR-based task presentation. Two individuals with ASD and two people with TD were in the group. Students wore eye tracker goggles while sitting in front of a computer screen to monitor the stimuli shown on the screen. Figure out how many times the researcher looked at two different AOI faces and two different settings. According to their findings, children with ASD exhibited less fixations on their faces, with ASD1 accounting for 30%, ASD2 accounting for 26.16 percent, TD1 accounting for 79% and TD2, 75% of those with ASD.

The researchers wanted to refine and verify eye tracking-based assessments for the examination of autism spectrum disease, and they also wanted to identify the severity of autistic symptom in the participants. The data was collected with the use of a SMI Red250 remote eye tracker. The participants were shown a five-minute film that had 44 dynamic stimuli, and the experimenter recorded their eye-tracking movements throughout the video. They employed statistical analysis of gaze patterns to arrive at their conclusions. The results revealed that the accuracy of ASD diagnosis was 0.86, or 95 present [19].

Wagner, J. B., et al. [20] examined the behavioural, neurological and autonomic aspects of facial emotions for persons with ASD and TD by employing eye-tracking and event-related potentials (ERPs) (ERPs). The eye-tracking and electroencephalogram (EEG) were employed in this investigation. The subjects were 18 with ASD and 20 TD. The eye-tracking stimulus is consisting of images of five female faces, each displaying terrified, cheerful, or neutral emotions. The Participants were placed on a chair in front of Tobii T60 display and the photographs seen for 5 second each. They observed that there was a link between gaze behaviour and emotions.

The eye-tracking technique was employed by Ahtola, E., and colleagues [21] in order to enhance babies' reactions to complicated visual stimuli while they were being monitored with EEG. A total of 39 male and 17 female typically developing newborns were studied with the Tobii T120, utilized to acquire the information. Wave gratings with a spatial frequency of 0.45 degrees and a temporal interval of 0.45 degrees were used as the stimuli for the experiment. During the visual stimulus, eye tracking and EEG were concurrently recorded in the child's lap by the parent. The responses of 39 healthy toddlers to the orientation reversal were 92%, 100%, and 95% of the stimuli given after statistical analysis (p0.01)..

Wei, W., et al.[22] introduced a novel approach for detecting In order to determine the fixation of ASD children and locations in images, we employed a combination of multi-level features and close monitoring. This dataset, which included 300 images of ASD and TD and was acquired by MIT using eye-tracking technology, was fed into the CNN. As it turns out, the accuracy rate is 88.18%.

Jiang, M., et al. [23] created a machine learning model to compare the eye fixation patterns of persons with ASD and Tourette's syndrome. Their research, "Atypical Visual Saliency in Autism Spectrum Disorder Quantified via Model-Based Eye-Tracking," was based on the data obtained by Shuo Wang and colleagues. The sample consisted of 20 high-functioning people with ASD and 19 individuals with TD. The photos were classified using DNN and SVM, which were developed by the researchers. DNN had the greatest accuracy, at 0.92 percent, and had the best overall performance.

Duan et al[24] used the SPCA database, which includes 500 images of 13 children with ASD, to generate their predictions. [24, 25]. They built the DNN model by comparing the performance of Salicon, SalGAN, Mlnet, SAM-VGG, and SAM-ResNet with those of five alternative techniques. Data was gathered using a Tobii T120 camera. A total of 50 images were used in the experiment, which was split into 10 sessions and administered to the children at random. Eye-tracking data was collected throughout each session. The most efficient algorithms were found to be: (AUC 0.8843) SalGAN in the healthy group, whereas SAM-VGG in the group with ASD (AUC 0.8843) generated the greatest results (AUC 0.8843). In the best case scenario, the AUC was 0.8178.

Tan, Y., et al. [25] employed CNNS algorithm for autism spectrum disorder and TD classification, with the fixation point's scan-path being used as the basis for the categorization. The data was taken from the Saliency4ASD grand challenge, and it comprised of 300 photographs taken by fourteen people with autism spectrum disorder and fourteen people with Tourette's syndrome. The accuracy of the categorization was 74.22 percent as a consequence of the process.

Using a face expression identification test, Jiang, M., et al. [26] studied the normal visual attention of persons with ASD and TD in a laboratory setting. The participants ranged in age from 8 to 17 years old and included 23 people with ASD and 35 people with TD. It eye tracker, and it contained a video of diverse emotional responses on people's faces, as well as an eye-tracking clip from the Tobii Pro. As part of the challenge to identify emotions based on facial expressions, the machine learning technique was used. They found that there was a statistically significant difference between the two groups when it came to eye movements. A classification accuracy of 86 percent was achieved with the usage of a deep neural network.

A machine learning approach was employed by Dalrymple, K. A., et al.[27] to categorize two sets of children, 37 children aged 18 months and 36 children aged 30 months, into two categories. Static Stimuli were shown to the youngsters by the experimenter, who then utilized an eye-tracking equipment, the Tobii TX300, to capture their eye movements. They employed Deep Learning classification to classify the fixation maps based on the number of fixation maps. Those under the age of 18 months were more interested in the dark portion, while those under the age of 30 months were more interested in the bright area. The classification accuracy was 0.70.

Using visual information taken from face stimuli to evaluate the utility of emotion detection, Król, M. E., et al. [28] using visual information from face stimuli, a new method was devised to evaluate the value of emotion detection. The eye movements of 21 autistic children were employed to construct the system. Stimuli included 36 photos of men and women, which were shown to the students. A SMI RED250 Mobile camera was used to capture the eye-tracking data. For example, "What is the emotion in the facial expression?" and "Which feature is broader?" were some examples of questions that prompted the presentation of an image. There were a variety of question-answer pairings to choose from. The results of this study show that the ASD group focuses more on the lower parts of the face and less on the eyes than the TD group.

B. Vocalization Technology

Early identification of Autism Spectrum Disorders (ASD) has emerged as a high priority research area as the incidence of ASD continues to rise. Early intervention has been shown to boost the likelihood of long-term success. Because abnormal communication is a distinguishing feature of ASD, automated acoustic-prosodic studies have gained a great deal of interest. Existing research, on the other hand, has mostly concentrated on verbal children, often older than three years of age (when many children may be properly identified) and as old as early adolescence. This paper presents the results of an acoustic-prosodic study of pre-verbal vocalizations (such as babbles and screams) of 18-month old

Tenenbaum, E. J., ., et al[29] According to preliminary results, an iPad app that measured autism risk behaviours discriminated between children with ASD and those who did not have the disorder at all. We wanted to see whether we could tell the difference between children with TD, DLD, and ASD based on the sounds they produced while using the app. While watching videos on ASD, the tablet's camera and microphone were used to collect participants' replies. Audio coding in the background Nonsyllabic vocalizations were more common in the ASD group than the TD or DLD groups, although syllabic vocalizations were more common in the ASD group. Nonsyllabic vocalizations were shown to be associated with autism spectrum disorder (ASD) 24 times out of 100. Early vocalizations in toddlers may be detected using tablet-based software, which is consistent with recent research showing that early vocalizations can assist identify ASD risk in toddlers. in Autistic Res. WP Inc. numbered 1–10.

Bedoya, S., Katz, ., et al[30] The acoustic study of toddler vocalizations, even for preverbal toddlers, has shown promise. Many conditions have been linked to babbling and speech like vocalizations. So far, pitch, energy, and voice quality have been investigated for early ASD diagnosis. Based on these results, we suggest the use of wavelet-based and speech modulation spectral characteristics for ASD diagnosis based on toddlers' screams, chuckles, and other noises. On a cohort of 43 18-month-old toddlers, a support vector machine classifier accurately distinguished the ASD group from the normally developing toddlers with accuracies over 80%, outperforming previous approaches. Worse, these new capabilities allowed vocalizations like screams, squeals, whines, and yells

Gong, Y., Yatawatte, et al[31] A realistic and entirely automatic ASD screening solution that can be implemented on such devices is shown in this study. The method records and analyzes a child's daily vocalizations at home, without the need for expert assistance. In order to test the efficacy of the suggested strategy, we conducted a 17-month study on 35 children, which revealed that we could get an un weighted F1-score of 0.87 for the categorization of normally developing and ASD children.

Xu, D., Richards, , et al[32] The LENATM (Language ENvironment Analysis) System assesses and tracks a child's vocalizations and speech using speech signal processing technologies. There are similarities between the adult phone-model and the kid clusters when it comes to child vocalization composition features. Error rates are reduced because to the integrated feature set. Because of this, 87.4 percent of records and 90.64 percent of children are detected at identical error rates.

Feng, M., Zhai, et al[33]This study's goal is to examine how babies with autism spectrum disorder (ASD) express dissatisfaction via vocalization. Up to 24 months, 48 ASD babies and 65 TD new borns were monitored for vocalization length and frequency.Atypical vocalizations in children with ASD might appear in both typical and social contexts at an early age, according to the findings of this study. There is a substantial correlation between the intensity of ASD symptoms and the relevance of the former in determining the outcome of ASD. Concerns and complaints from parents about their newborn's vocalizations

Chi, N. A., Washington, et al[34] this paper, offered a suite of machine learning algorithms for detecting autism in self-recorded speech audio obtained from autistic and neurotypical (NT) children in their natural contexts, including their homes. after being trained on a diverse collection of home audio recordings with varying recording quality, the models were successful in predicting autism status. This suggests that the models may be more generalizable to real-world situations. The findings suggest that machine learning approaches have potential in terms of autonomously identifying autism from speech without the need for specialist equipment.

Liu Min, Hu Yang, & Liu Qiaoyun [35] According to the perceptual orientation hypothesis, aberrant auditory processing of speech sound cues in children with autism spectrum disorder (ASD) prevents them from learning speech-like vocalizations, hence impairing the development of vocal complexity. According to social feedback orientation theory, the efficiency of the social feedback loop in children with autism spectrum disorder (ASD) is diminished. When a result, as the number of cycles of the social feedback loop reduces, the frequency of their speech-like vocalizations lowers as well.

Asgari, M., Chen, L., & Fombonne [36] This research presents an automated method for dissecting prosodic anomalies into fine-grained, quantitative metrics. We estimated harmonic content of speech using a harmonic model (HM) of spoken signal. Using these and other indicators, we effectively trained machine learning models to identify autism from regular development (TD). Our models outperformed a random model in diagnosing autism in a sample of 118 children (90 with autism and 28 without; mean age: 10.9 years). Voice and speech analysis might be used to screen preverbal newborns and toddlers for autism.

Min, C. H., & Fetzner, J. [37] This study detects vocalizations using deep learning neural networks. The algorithm may be taught to recognize non-speech vocalizations of autistic children by comparing comparable data from other recorded human voice. The suggested approach may distinguish nonverbal autistic children's stemming from background noise by recognizing vocalizations.ASD patients' homes are now being evaluated for the deployment of this technology, which is currently undergoing institutional review. A system like this might be used to aid physicians and therapists in tracking the progress of a patient's therapy.

Tenenbaum, E. J., Carpenter,et al [38]a A tablet-based application that assessed numerous signs of autism spectrum disorder (ASD) was able to distinguish between those children who had the disorder and those who did not. We investigated whether the vocalizations made by children between the ages of 16 and 31 months with normal development (TD), linguistic or developmental delay (DLD), and autism spectrum disorder (ASD) might be used to make a distinction. Using a tablet's camera and microphone, researchers were able to record participants' visual and vocal responses while they watched movies that were designed to elicit ASD-related behaviors. Vocalizations are coded offline. For children with ASD or DLD, the rate of nonsyllabic vocalizations was greater among those with ASD than among those with TD or DLD, and the ratio of syllabic to total vocalizations was higher among those with TD than among those with ASD or DLD. b. ASD was shown to be 24 times more likely in children who made nonsyllabic vocalizations. They corroborate previous studies showing the ability of using a tablet-based scaled application to monitor vocalizations during a regular pediatric checkup to determine ASD risk.

Heath, C. D., McDaniel,et al [39] Researchers looked at the best ways to inform parents, teachers, and other caregivers on how to provide therapy themselves. It takes a long time to complete these programs, and there is often little follow-up support. Use technology to examine how educational and support processes might benefit from it. The training methods, participants, and durations stated in scholarly articles and publicly available training programs were studied. These items demonstrate the importance of making programs more accessible. The study of computers and software allows us to see how training and support programs might be made more user-friendly. It is clear from studies and community-based training programs that teaching ABA skills is a challenging undertaking. In the future, advances in multimedia data processing and machine learning may reduce the need for ABA tutors and other human resources. Using machine learning, video probes of realistic ABA treatment implementation might lower the human cost of fidelity assessment and benefit those interested in the treatments. In the future, these technologies may be used to obtain more information regarding treatments.

Lee, J. H., Lee, et al [40] In this paper, they introduced a pre-trained feature extraction auto-encoder model and a joint optimization scheme that can achieve robustness for widely distributed and unrefined data when using a deep-learning-based method for the detection of autism that incorporates a variety of models. According to the findings, we may diagnose autism spectrum disorders in newborns with better accuracy using an auto-encoder-based feature extraction and joint optimization approach using the extended version of the Geneva minimalistic acoustic parameter set (EGeMAPS). Check Out the Whole Thing

Eni, M., Dinstein, I., Ilan, et al [41] A group of Hebrew-speaking students who have taken the ADOS test contributed their prosodic, acoustic, and conversational features to this research. Researchers analyzed the recordings of 72 youngsters and found 60 traits that were associated to the children's ADOS scores. When it came to responding to the clinician's questions, the speed and quantity of vocal responses were shown to be inversely connected with pitch variability and ZCR. DNN techniques were developed for ADOS estimation and compared to Linear Regression and Support Vector Regression (SVR) models. A Convolutional Neural Network (CNN) produced the best results (CNN). This technique predicted ADOS scores with a mean RMSE of 4.65 and a mean correlation of 0.72 when trained and assessed on multiple subsamples of the available data. Early identification, assessment of symptom severity, and evaluation of treatment efficacy might be revolutionized by the development of automated algorithms that accurately anticipate the severity of ASD.

Narain, J., Johnson, K. T., Ferguson, et al[42]In this paper, we offer a speaker-dependent categorization of these real-world sounds for three nv/mv persons as well as an interactive application to interpret nonverbal vocalizations in real-time UARs of 0.75, 0.53, and 0.79 for the three individuals were achieved using support-vector machine and random-forest models in this study. A commercial wearable microphone and a smartphone were used to test the feasibility of real-time binary categorization of nonverbal vocalizations. Non-traditional communicators may benefit from customised machine learning strategies based on this study.

Neimy, H., Pelaez, M, et al[43] This study replicates and extends previous research by increasing both vocalizations and echoics in three infants at risk of autism spectrum disorder (ASD) while they are with their mothers in the natural environment, using contingent social reinforcement procedures (such as vocal imitation and motherese speech). At-risk infants who were exposed to contingent reinforcement (particularly vocal imitation), as well as high rates of vocalizations and echoic approximations, were shown to acquire pure echoic repertoires.

Narain, J., Johnson, K. T.,et al[44] study Vocalizations that are not spoken verbatim, such grunts, sighs, and monosyllabic sounds. has mostly focused on the social and emotional consequences of these sounds when they are used in conjunction with traditional speech. Individuals who do not utilize standard speech, such as those with non- or minimally verbal (nv/mv) autism, may benefit from the information included in these vocalizations since it is significant and individual-specific emotional and communicative information. It is described in this study how nonverbal vocalizations from nv/mv humans in natural situations are produced, perceived, and decoded using various methodologies, analyses, and technological advances. We are working on innovative signal processing and machine learning approaches that will aid in the development of augmentative communication technologies. We are also creating a nonverbal vocalization dataset that will be made available to the public.

Sandercock, R [45] The current research looked at newborn vocal response to adult social partners as a putative pathway linking early attention deficits to later language ability and ASD symptom presentation. Children with heightened genetic risk for ASD were split into three groups: those with ASD diagnosed later (HR-ASD), those without ASD diagnosis (HR-neg), and those without a known family history of ASD (HR-neg) (LR). Contrary to expectations, the HR groups outperformed the LR groups at 6 months. Language results were connected to attention at 6 months but not 12 months, indicating a transition period between the HR-neg and HR-ASD groups. At 12 months, the HR-ASD group was less likely than the HR-neg and LR groups to respond vocally to adult vocalizations. A greater contingency probability suggested a decreased chance of a positive ASD diagnosis. Following these results, pre-diagnostic intervention targeting contingent responsiveness may be an option for babies with a genetic vulnerability to ASD. These findings point to a method by which early ASD risk factors may be increased, leading to cascade social-communication issues.

C. Deep lrearing methods

Liao, D., & Lu, H. [46]suggested a unique approach to objectively diagnose autism disorders and normal participants. The approach identifies community structure in each subject's network. The NMI statistic matrix was created and then loaded into denoising autoencoder to categorize. It worked on three datasets. Our technique outperforms the old one in terms of accuracy. Our approach is also faster than importing Pearson correlation matrix into classifier. Our technique helps clinicians objectively identify autism.

Khodatars, M., Shoeibi.,et al[47] Present important challenges in the automated detection and rehabilitation of ASD and propose some future works.It may be difficult to provide optimal strategies for ASD diagnosis using neuroimaging data without relying on sophisticated AI techniques like DL. The use of DL networks in research to distinguish ASD is studied in this study. The rehabilitation methods available for ASD patients who use DL networks are also evaluated.

Wang, H., & Avillach, P. [48] Deep learning models may be employed with common variants since this research found significant common variations that may be protective or detrimental for ASD, as well as their additive contribution to ASD. Predictive classifiers for ASD diagnosis were then created using deep learning prediction algorithms based on the frequency of alterations found. With the use of a holdout test data set from the Simons Simplex Collection (SSC), the researchers were able to confirm their results and show that the proposed strategic approach worked best in differentiating the ill from the control groups.

Ahmed, I. A., Senan.,et al,[49] this job imply This study developed three artificial intelligence methodologies for early autism diagnosis: machine learning, deep learning, and a mix of the two. The first methodology, neural networks, uses a hybrid method combining LBP and GLCM algorithms to classify features. This method achieved 99.8% accuracy for FFNNs and ANNs. The second technique used a pre-trained convolutional neural network (CNN) model like GoogleNet or ResNet-18 to extract deep feature maps. Each model outperformed the other by 93.6 and 97.6%. With last, GoogleNet + SVM or ResNet-18 + SVM coupled deep learning (GoogleNet) and machine learning (ResNet-18) (SVM). This approach requires two blocks. To extract deep feature maps, the first block utilized CNN, while the second block used SVM. This method's diagnostic accuracy was 95.5 percent for GoogleNet + SVM and 94.5 percent for ResNet-18 + SVM.

Heinsfeld, A. S., Franco.,et al,[50] Researchers in this study hoped that by studying the brain activity patterns of autistic patients, they may apply deep learning algorithms to identify people who suffer from autism spectrum disorder (ASD). From the ABIDE database, which is a worldwide, multi-site database, we examined the brain imaging data of ASD patients (Autism Brain Imaging Data Exchange). There are several symptoms of ASD, including repetitive behavior and problems in social situations. The Centers for Disease Control and Prevention estimates that one in every 68 children in the United States is affected by ASD. Using functional brain imaging data, we looked at patterns of functional connectivity that may be used to objectively identify people with ASD. We also looked at neural patterns that emerged as a result of the categorization as well. The researchers advanced the state-of-the-art by correctly classifying 70 percent of the dataset's control patients as having ASD. There is an anticorrelation of brain activity between the anterior and posterior hippocampus, which is consistent with the theory that ASD is characterized by abnormalities in the anterior-posterior connections of the brain. According to our deep learning model, the areas of the brain that helped differentiate ASD from normal development are depicted.

Leming, M., Górriz, J. M., & Suckling, J. [51] A convolutional neural network was trained using the largest multi-source functional MRI (fMRI) connectomic dataset yet assembled (CNN). This approach allows for cross-sectional comparisons of ASD and TD outcomes. We categorize the data by gender and by job versus rest in order to put them into perspective. It was possible to train 3300 modified CNNs in an ensemble model using class-balancing, which allowed us to find fMRI connections between ASD and typical development (TD), as well as gender and the job at hand. For the black box problem, we'll employ two different visualization strategies. Class activation maps show the connections our models make in the brain while attempting to categorize. For the second time, we noticed that the model uses different areas of its hidden layers to process different covariates of data (depending on the independent variable analyzed) and other sections to mix in data from several sources. As part of deep learning models, the right caudate nucleus and paracentral sulcus are critical.

Xu, L., Liu, Y.,et al [52] First-order statistical features may be used to estimate the global time-varying behavior of brain activity using fNIRS time series. An extended bagging algorithm was used to build a convolutional neural network (CNN) model based on the integration approach with the enhanced bagging algorithm in order to explore the probable patterns of temporal variation for ASD identification. Hemodynamic oscillations in hemoglobin (HbO2) and deoxy-hemoglobin (Hb) were examined using the theory of stationarity to determine if children with ASD had lower internal logic than typically developing (TD) peers, but that TD children had better memory and resistance to random shocks. An accuracy rate of 97.1 percent and a specificity of 94.3 percent were achieved using the deep learning approach recommended for differentiating between ASDs and TDs in children.

Ke, F., Choi, S.,et al[53] There were 14 models, including convolutional and recurrent neural networks, employed to study the structural and strategic underpinnings of ASD. We utilized an open source autism dataset with over 1000 MRI scan images and a high-resolution structural MRI dataset to demonstrate how deep neural networks may be used to detect and assess mental illnesses. Convolutional neural networks (CNNs) were used to exhibit combinations of brain regions, showing which areas were more commonly used to categorize images. Using recurrent neural networks, we were able to classify the brain's regions in the correct order. Our categorization procedure yielded a wealth of structural and strategic data that is critical to the model's success. Subcortical areas, such the basal ganglia, have been linked to structural and strategic evidence, for example (BG). Finding the various brain areas that identify a complex mental disease while simplifying doctors' deductive reasoning provides a cost-effective and time-efficient diagnostic process

D.Result

The results differ from one research to another. The results depend on the accuracy of the diagnosis using a specific technique, but most of the results obtained are good results with the difference in the accuracy of the diagnosis. We would also like to point out that the use of two methods at the same time, for example, the method of eye tracking and magnetic resonance imaging, is more accurate. At a high rate, that is, using more than one method leads to more accuracy .The experimental findings revealed that the use of a visual representation might make the diagnostic process easier while still achieving high levels of precision. In particular, the convolutional neural network model has the potential to attain a high level of classification accuracy. This strongly shows that visuals are capable of encoding the information contained in gaze motion and its underlying dynamics correctly. On the basis of the maximum information coefficient, we looked into potential links between the severity of autism and the kinetics of eye movement. According to the results, the combination of eye tracking, visualization, and machine learning has significant promise for development of an objective tool to help in the screening of autism spectrum disorders (ASD).

E.CONCLUSIONS

While the bulk of the publications assessed have focused on eye-tracking technology, this review article has covered research on autism detection combining eye-tracking and vocalization technologies. Researchers used eye-tracking software to acquire data on eye fixation and eye-tracking maps while seeing visual dynamic stimuli or static stimuli. Two groups of youngsters were studied: those with autism and those developing normally. Eye-tracking heat maps were generated using Deep Learning, while statistical analysis of fixation data was used in some of the trials under consideration, according to the researchers. While autistic children were less interested in features and eyes, they were more interested in the mouth, the body, and the background, compared to children who were not autistic. Children's and adults' vocalizations were also examined by the researchers in this study in order to detect autism. For the most part, researchers employed deep learning approaches to compare two distinct groups of children with ASD and TD.

Abbreviations

No	Abbreviations	The meaning
1	**ASD**	Autism Spectrum Disorder
2	**TD**	Typically Development
3	AOI	Area Of Interest
4	DNN	Deep Neural Network
5	SSC	Simons Simplex Collection
6	CNN	Convolutional Neural Network
7	SVR	Support Vector Regression
8	DD	Delayed development
9	EEG	Electroencephalography
10	ERPs	event-related potentials ERPs
11	LENA	Language ENvironment Analysis
12	EGeMAPS	Geneva minimalistic acoustic parameter set
13	MRI	Magnetic Resonance Imaging

Availability of data and materials

All materials and data have been provided from solid research published in international journals, as indicated in the sources below.

CONFLICTS OF INTEREST

The authors declare no financial or other conflicts of interest.

Funding

The author acknowledges that the wider study from which this paper is generated is financially supported by author himself and there no other government entity or nongovernment support this work

Authors' contributions

All authors were involved in revising and approving the manuscript.

Acknowledgments
My thanks and gratitude to Professor Dr. Shaima Hamid Shaker for her continuous support, review of all work, and dedication to performing her duties.I also extend my thanks and gratitude to everyone who participated in his research and work in the service of society

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