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Automations in the Screening of Autism Spectrum Disorder

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Abstract. The Autism Spectrum Disorder (ASD) is known to be characterized by decreased social interactions to stimuli, difficulties in communication, repetitive behaviors and physical movements. Since it affects different individuals differently and to different extents, it is very challenging to diagnose and differentiate from other neurodevelopmental disorders. Research shows that early intervention can be very beneficial in the long term as the affected individuals' symptoms can be reduced to a great extent , but the lack of awareness and objective diagnostic tools makes it difficult to diagnose at an early age. In this paper we explore the various innovations made in automating the screening process by listing the demerits of the subjective existing diagnosis systems and also surveys and complies the various eye gazing, voice prosody, wearable IoT modules, their contributions and their impacts in making the diagnosis process of Autism Spectral Disorder more objective and efficient.

Keywords: Autism Spectrum Disorder, Automatic Screening, Eye Gazing, Voice Prosody, Static IoT, Wearable IoT, Automation in Diagnosis, Annotations of Data, Machine Learning in Biomedical Sciences, Repetitive Motor Movements in ASD, CARS Rating System.

1. Introduction

Autism Spectrum Disorders (ASDs) are categorized as neurodevelopmental disorders whose characteristics are diminished social interactions to stimuli, troubles in communication, repetitive behaviours and physical movements or unusual or severely limited interests [1]. As of 2016, "about 1 in 54 children has been identified to be on the autism spectrum according to estimates " from CDC's Autism and Developmental Disabilities Monitoring (ADDM) Network and this number is on the rise.

When we say that autism is a spectrum disorder, it means that it manifests itself on a broad band of impairment, the most extreme end of which is being diagnosed with ASD; and Pervasive Developmental Disorder (PDD-NOS) representing the milder end of the spectrum. Theoretically, there is no way to differentiate between PDD-NOS and autistic disorder and hence PDD-NOS as a diagnosis is used as an exclusion condition when all the conditions for autistic disorder are not met. These ambiguities exist due to the absence of a universally standardised cutoff for autistic disorder.

Research indicates that if we manage to diagnose it early on in the individual's life, it is possible to create positive changes in developing the individuals' skills [2, 3, 4, 5, 6] by designing a specific intervention protocol and the sooner this is done, the more chances exist of them making progress. Rarely they will make enough headway that they don't show up on the spectrum anymore. Autism Spectrum Disorder (ASD) can sometimes be diagnosed in children before they are 2 years old and an early intervention protocol should be followed at this stage as the young child's brain is still forming [6].

The screening of Autism Spectrum Disorder to this date, remains a very intimidating endeavor considering the subjectivity of the tests involved and the rigorous hours of inspection needed[7]. The objective nature of the automated approaches to the screening of Autism Spectral Disorder would be perfect as a second opinion and by an extension also a viable screening process after which the patients would be referred to a professional accordingly. Tests like eye tracking, detection of physical attributes via wearable and static IOT devices, classification on MRI scans and voice prosody detection techniques[8] are easily reproducible and more time efficient than a one on one interview session with a therapist.

One of the primary advantages of automating the screening process is the detection of attributes that are invisible to the naked eye, for example the fixations and saccades [7, 9] of an individual encodes a lot of information about their oculomotor control , attentivity and personal psychological factors. Some automations like LENA or Google Glasses have also enabled the researchers to observe patients in their natural environment. The real time feedback associated with these technologies can also be used to fine tune the device to minimize the margin of error. Annotating videos automatically would reduce the manual workload of the therapists and empower them to serve their patients better [10, 11, 12].

In this paper we delve deeper into the advancements made to automate the screening process of ASD. The structure of the paper is divided into 5 sections. Section 2 describes the existing subjective system used for diagnosis. Section 3 deals with the Eye Gazing Modules and their contribution in the screening of ASD. Section 4 deals with the Voice Prosody Module and Section 5 deals with the Static and Wearable IoT Devices, the insightful readings and their importance for the detection of ASD in children. Section 6 concludes the paper.

2. Existing Systems

Currently, the practices being followed to screen and diagnose potentially autistic children include the involvement of clinical practitioners, speech therapists and specialists. Clinical practice usually recommends the use of widely accepted standards and protocols along with the subjectivity of the specialist's experience and judgement. That being said, the absence of an ASD cut-off on several widely used diagnostic testing tools and questionnaires means that most ASD diagnoses are made principally from medical experience with negligible backing from the screening devices itself. One of the assessment tools for detection of autism spectrum disorder is the Childhood Autism Rating System (C.A.R.S) [13]. This system is a behaviour rating scale which is used by comparing the child's conduct, characteristics and aptitudes with that of normal growth of a characteristic child and hence giving ratings based on it. It can be administered on children above the age of 2 years and it consists of 15 items spread across the domains of 'relating to people' and 'emotional response', on which the ratings are given. The scores for each item range from 1 to 4 representing normal behaviour accordingly to the patients age and 4 representing severely abnormal behaviour for the child's age. After all the ratings are given, the summation of all gives the total score which is compared against the cut-offs. A score within the 30 to 36.5 range denotes slight to modest autism, and anything above 37 denotes extreme autistic tendencies.[14]

Even though it is extremely sensitive, the CARS at times over-diagnose individuals as having autism. One of the limitations of CARS is that the distinguishing of ASD on the score of 30 was not empirically tested enough, hence it is not reliable. In actuality the CARS cannot differentiate between PDD-NOS and ASD, or the extremities of the Autistic Spectrum[15]. CARS is not a standardised procedure and it is not independent of clinician's subjectivity. Many of the experiments done to examine the agreement of the CARS cut-offs have been performed using data provided by parents or caregivers rather than actual observation. Even when the observations are made, it is difficult to observe problematic behaviour in short visit hours by clinical practitioners.

The Diagnostic Interview for Social and Communication Disorders (DISCO) is an interview based assessment method which is conducted by experienced medical practitioners. The DISCO is a detailed semi-structured interview which gives the interviewer an idea of the entire life of the interviewee right from their formative years to the current day. It uses a dimensional approach to assessment rather than using arbitrary cut offs and tries to place individuals in distinct categories. This approach is far more helpful for understanding the needs of the individual and charting an intervention plan. Most importantly, there needs to be someone who can objectively explain all the characteristics of the child with respect to the domains of the assessment and in some cases this may not be possible. It also gives information regarding other potential developmental, psychological or psychiatric disorders. It consists of 85 items classified under two broad domains: social-communication and limited and repetitive behaviours.

A study [16] was conducted to discern the most influential or essential features that played the biggest roles in diagnosing autism spectrum disorder. Fourteen factors were recognized that significantly differentiated between the patients suffering from ASD against those who are not, most of which were from the socio-emotional trade-off category broadly classified under the social- communication domain (from which 11/14 characteristics were identified). Thanks to the wealth of information that can be generated about an individual using DISCO, other underlying related comorbidities can also be brought to the surface. Further studies should include discerning the essential features required to differentiate between other psychological and mental issues like ADHD, Asperger's syndrome and Autism Spectrum Disorder rather than focusing on a binary outcome of "ASD" or "Non ASD".

3. Eye Gazing Model

Autism Spectral Disorder is branded with uncharacteristic responses to visual stimulus. The visual response of children to various seemingly normal visual stimuli and their dissonant response from the normal is a characteristic trait of Autism Spectral Disorder. Research done in papers like [17] corroborate the claim that children suffering from Autism Spectral Disorder are unable to respond typically to visual stimuli. Hence, Eye Gazing technologies can play a very vital and efficient role in an early screening of Autism Spectral Disorder.

There are several eye gazing technologies like the Tobii T120 Eye tracker (used in papers [18, 10, 19]) and SMI Red mobile (used in papers [8]) that measure various attributes like Gaze position, Pupil, Distance, Validity, Blink rate, Blink duration, Pupil Diameter, Fixation duration, Fixation rate, Saccade duration, and Scan paths [10, 19]. These attributes can be used to classify ASD and TD patients.

In [8] the novel scan paths are developed by the fixations and saccades of the participants. Each fixation point is connected and joined by a colored line, the color of which depends on the

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saccade. A higher saccade signifies a higher velocity between the fixation points and a lower saccade signified a lower velocity. The RGB values of each line were corresponded with Velocity, Acceleration and Jerk respectively where a higher value would result in a darker shade. Thus, the scan paths that were not quite so informative, after this transformation were converted into a novel scan path that conveyed more information. After preprocessing of the scan path like resizing and gray scaling a logistic linear regression model was trained on the data which resulted in an AUC of approximately 0.819.

The availability of an open dataset like the ones provided by [18] is very essential for advancements in research done on visual patterns and their significances in the screening of ASD. In [18] a dataset of eye movements of 14 patients suffering from ASD and 14 healthy controls on 300 different images is made available publically at **http:// doi.org/ 10.5281/zenodo.2647418**. Every image from various categories was displayed for 3 seconds with a second gray mask interval. Adequate calibration on the Tobii Eye Tracker 120 of every participant was done before the experiment was conducted. The participants were asked to view the images freely and their corresponding eye movements were recorded. The heat maps generated of all the participants suffering from ASD vs their healthy controls revealed some very interesting revelations. For object level features in an image there was very little difference observed between the heat maps and on the contrary for low level features in an image a vast difference was observed in the heat maps of the two groups. There are several more visual features captured and presented in the open dataset that can be exploited by researchers.

The authors of the paper [18] have made another dataset available publically in [20] which was used in the paper [10]. In the paper [10] the authors utilize low and high level saliency maps extracted from the open dataset to establish a classification between ASD and TD(typically developing) participants. First an additional level of gaze feature extraction was employed to infer additional data from the given scan paths. These features included basic fixation statistics and some inferred saccade amplitude statistics. Previously done research in [21, 22] had considered only low level saliency heat maps to distinguish between ASD and TD participants. This paper improved on their work by also testing high level saliency heat maps to find a clear classification between ASD and TD participants. The classification model reported an AUC of 75% with a confidence Interval of 95%.

These papers demonstrate very efficiently the importance of the eye gazing module in the early screening of ASD. Not only can the eye gazing module be utilized for an early screening of ASD but the information conveyed and interpreted by these modules can also be used in some very crafty and handy applications. A virtual reality driving system for patients suffering from Autism Spectral Disorder has been developed by the authors of the paper [19]. This system uses eye gazing technology like the Tobii Eye Tracker to calculate the cognitive capacity of the individual in real time. Accordingly, the difficulty of the program is adjusted thus making it not only optimal but also catered to every individual suffering from this illness. Thus, eye gazing modules not only help reveal the cognitive load, capacity and feedback for an individual [23, 24] but have also assisted researchers in developing systems that assist patients suffering from ASD to learn driving skills.

A similar application of the eye gazing module to assist patients suffering from ASD has been done by the authors of the paper [25]. A typical social and communication skills are the trademark of ASD and more than often these may be misconstrued by an interviewer who is unfamiliar with this condition. Thus in this paper the authors have created an application that would work with Google Glasses to help ASD patients in giving a job interview. The application Little

Helper measures attributes like volume and interviewer in frame and accordingly suggests the patient the appropriate action. Although this application is still in its primitive stage with only two attributes and can be used effectively only for a singular interviewer, it is a step in the right direction.

Thus, clearly the eye gazing module has had several breakthroughs and in the coming years will be one of the most crucial components in the screening of ASD.

4. Voice Prosody

According to the DSM-5, over-sensitivity or under sensitivity to sensory stimuli or strange responses to the stimulus and the environment around the patient is defined as either a limited spectrum of reactions or a repetitive pattern of behaviour. In either of the cases, these are keen indications of Autism Spectral Disorder and the patients must be made to undergo a screening process. Individuals with autism show an unnatural reaction to sensory inputs, in that they show differing issues in their perceptions of such inputs. [26]

Coming to the voice prosody of affected children, it is a known fact that most of them have abnormal intonation characterized by monotonous speech and in some cases, inappropriate accents. A comparative study between the performance of a voice analysis trained model and experienced speech therapists on single word utterances by the control group of unaffected children and children affected by the autism spectrum disorder revealed that the machine learning model outperformed the speech therapists [27] This study focuses on pitch, a crucial part of the voice prosody. All 24 separate features of pitch were used to calculate the F-measure. Future research could be directed in the area of determining how many of these 24 features could be most important factor in voice based analysis. Voice prosody however, is made up of several other speech elements besides pitch such as rhythm and stress. Further clarification of abnormal prosody in ASD could be provided, for which the machine learning voice analysis may be better suited to providing objective standardised judgements rather than speech therapists by analysing elements of prosody other than pitch.

The caveat of this study is that machine-learning-based classifications would be easier on single-word by making the job for the classification model a lot simpler by reducing the complexity of the input. The clinicians are at a started disadvantage for this is very limited data to work upon. Since clinicians generally rely on extensive speech samples dwelling in a varied semantic, syntactic, and grammatical data to make their judgements, the single word utterances put them on the back foot. Keeping this in mind, the voice analysis model adds the much-needed objectivity to gaging prosody. This method is bound to be impactful in both the screening of Autism Spectrum Disorder and further research on the important factors in determining the same.

5. Static and Wearable IoT

The importance of computing and its impacts cannot be better illustrated than what is done by the authors of [28] Wearable on body sensors along with static sensors can be utilized to infer some crucial information about any patient. Not only does this help us capture features invisible to the naked eye, but it also facilitates researchers to observe the patient in his/her natural environment. Behavioral Imaging via the use of IOT devices can help researchers understand and model Dyadic interactions better and screen patients suffering from ASD quicker. The authors of this paper have also released an open dataset called the Multimodal Dyadic Behavioral Dataset. This dataset contains sensor collected and annotated data of children in a Rapid Abc protocol which is an interactive informal test conducted by an examiner to deduce any socio-communication abnormalities if any in the paper [29].

The paper continues to illustrate the importance of the study and understanding of these dyadic relations and the significance of behavioral imaging to fathom these relations. The authors believe that advancements in behavioral imaging using interdisciplinary approaches would lead to a quicker and more objective process of screening of the Autism Spectral Disorder.

We have discussed the importance of early detection of autism spectrum disorder. Other early signs such as unusual kinematics of upper and lower limbs sometimes manifest in affected children and studying these patterns is especially important as they are observable before the speaking abilities of the child are developed. A study [30] in this space aimed at discriminating between High Risk infants and Low Risk infants was conducted using the SVM and ELM classification algorithms. The risk of Autism Spectrum Disorder was gaged by checking the family tree for any occurrences of patients suffering with ASD.

In this study, the two groups of infants were made to toss a ball into a plastic tub thrice and then, tested on their ability to insert a ball into a clear open tube. The study successfully classified children into the High Risk and Low Risk groups. This is relevant as it aims to study a behavioural pattern of autistic children quantitatively and does so at a very early age, as opposed to the time-consuming clinical methods of doing so using questionnaires and interviews.

It is also known that people suffering from Autism Spectrum Disorder commonly occupy themselves in repetitive motor movements and a convenient way to record and analyse these movements using lightweight and comfortable wearable sensors would help medical practitioners and caregivers to monitor this type of behaviour and hence come up with a more comprehensive protocol of intervention. The stereotypical movements include but are not limited to : body rocking, hand flapping and other complex hand and finger movements. Health researchers do not possess the effective tools to acquire accurate data with their timestamps and duration of such movements occurring in natural settings. This is where ubiquitous computer systems can be leveraged.

Six children with these tendencies were monitored using wireless accelerometers in a study [30] conducted in laboratory and classroom settings.The informant rating meters are subjective , often inaccurate and fail to apprehend the variations displayed by every patient suffering from ASD. Human errors are very common as difficulties arise in determining the start and end time of movements accurately, as well as determining the environmental antecedents for certain actions. Hence, this study successfully detected the movements automatically and accurately.

The paper [11] tackles the problem of the time consuming observational methods employed to detect children struggling with ASD [31] Using wearable IOT devices. They have enlisted the upcoming advancements in the technologies to measure social interaction like the author so the paper [32].

WHO, backed up by NASA created an interaction measurement system using wearable IOT devices. This system measures several factors like face to face time, proximity time and activity level which are all crucial indicators of a patient suffering from ASD. These factors are calculated in a classroom environments using wearable IOT like badges and ultrasound signals to calculate the proximity and the time the dyad is facing each other. Thus, this paper extensively covers the advancements done in the monitoring and collection of data to diagnose children suffering from ASD using wearable IOT devices.

The paper [12] also deals with the issue of collecting and monitoring of data. In this paper the authors develop a system of wearable dynamic and static IOT devices to record data and self stimulatory patterns like Hand Flapping, Punching, Drumming and Rocking. A therapist usually has to record all his sessions and manual logging and annotating of the data is required. This manual labor is also reduced by the system since the recording is started only after the required patterns are observed and background logging of the recorded data is conducted as well. The system includes accelerometers that could be stuck on to the patients knees, hands, elbows, neck, etc to record the (x,y,x) positions in real time. Static devices include a camera to record the video and a mike for audio recordings. The positions are sent to a PC in real time and accordingly when an activity is detected the recordings are started. A hidden markov model was used in the classification of the data collected by the accelerometers which detected self stimulatory patterns with an accuracy of 91.5%. This implementation not only uses the data recorded by the wearable IOT for classification but also uses it to reduce the video recordings while annotating it at the same time. This experiment was performed on 4 students and scaling this operation would categorically reduce the workload of therapists.

Thus IOT devices provide a very valuable insight into the screening of ASD alongside also assisting in the recording of additional data. Advancements in this direction are going to be monumental in the screening process of ASD.

6. Conclusion

The real world applications of machine learning are expanding at a rapid rate and in this regard, their use in detection of psychological issues is no exception. The advancements in automated techniques of screening autism spectrum disorder will bring in much needed objectivity in the space leading to more accurate results and eradicate the existing ambiguity thereby increasing the awareness among individuals that early intervention is the way to go if long term sustained improvements are to be achieved.

This paper surveys and analyses the existing systems and their shortcomings while at the same time acknowledges the advancements made in the right directions. In the automation space, all the discussed modules have been tested in an isolated manner and further research needs to be conducted in the direction of testing all these modules together on the same dataset to build a robust, comprehensive, objective, time and cost efficient screening and diagnostic system. This would act as the cornerstone in autism spectrum disorder diagnosis and understanding the behavioral patterns for future studies, keeping in mind the huge scope that exists in the machine learning and automation space along with sophisticated statistical methods and models.

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