Artificial Intelligence in Autism Assessment

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Abstract—The current paper review gives a brief and representative description of the role that artificial intelligence plays nowadays at the assessment of autism. Therefore, many researchers note that artificial intelligence plays a notable role in the early diagnosis of autism since it helps the clinicians shorten the diagnose process and have more accurate results. Thus, the research team of this paper presents some applications of artificial intelligence that are used already or are in a preliminary phase aiming to highlight the use of smart technology in the diagnosing process of autism. Lastly, it is worth noting that an early and accurate diagnose is the key point for an individualized and successful intervention which aids the academic as well as the personal development of the child.

Keywords—Artificial intelligence, autism, assessment

1 Introduction

Autism is a neurodevelopmental disorder and the traditional methods of diagnosis include screening scales, interviews, and clinical observations. It is mainly based on the analysis of the behavioral patterns through questionnaires that are filled by the parents or the guardians. A very popular tool that is used is ADOS, which is a semi-structured evaluation of the communication, the social interaction and the imagination that is designed to diagnose children who belong at the autistic spectrum [1]. Autism is a pervasive developmental disorder since it affects the person during all the periods of its development. The characterization "pervasive" declares that the disorder affects globally the development of the person [2] and the term "disorder" expresses the sense of differentiation from normal. The fact that autism is a by birth disorder doesn't mean that the symptoms are obvious from the first moments of the child's life. Usually, they become apparent before primary school.

The age of four is the average age of the diagnosis of autism in the USA. By this time, the developmental stage that early intervention has the greater results has already passed. In particular, for the children who weren't diagnosed before the age of 8 years, the possibility of therapeutic intervention has been greatly reduced. Therefore, the goal is to apply earlier the evaluation tools and the classifiers [3].

The children who belong at the autistic spectrum present a variety of behaviors that differ from each other. This fact makes the diagnose process even harder since it is difficult to create behavioral models that interact socially with these children. Also, there is a lack of specialists and a clinician might feel uncertain during the diagnosis. Therefore, there is a need for computational systems that have the abilities of a clinician and help the already existing diagnose methods by confirming the evaluation decisions of the doctors [4].

Additionally, the data for autism (1 child at 68) are based on studies from 2014. Nowadays, the real data might be even higher. This is happening because the waiting time for a diagnosis at the rural regions with a low social and economic status is even longer than the average. Hence, the real size remains unknown globally [5]. Also, the cost of health care of people with autism is exorbitant and if we combine it with the long waiting time for a valid diagnosis, we realize the necessity of creating applications and methods of collecting data faster [6].

Therefore, as we mentioned above, the already existing diagnostic tools demand a lot of hours of waiting and evaluate a small percentage of cases [7]. Also, since the symptoms are altered through time and re-evaluation is needed, the whole process can become monotonous and tiring for the children and the parents. In addition, the scales are not entirely objective so the results can be mistaken [8]. This burden can be ameliorated by using artificial intelligence, a novel way to improve accuracy and effectiveness during the detection of autism.

Artificial intelligence is related to the design of computational systems that mimic human behavior but also have the capabilities of learning, adjusting, understanding the environment and solving problems. According to John McCarthy, who is the founder of the term "artificial intelligence", AI is the science that involves the creation of intelligent machines. A remarkable definition is "the study of ideas that allow the machines to be smart" [9]. Artificial intelligence is not limited in executing simple orders but is able to automatically execute complicated tasks that take a lot of time and effort for humans [10].

In this project, we will try to present a short introduction about the role and the contribution of artificial intelligence in the diagnosis of autism. Afterward, we will list some of the researches that mention useful AI applications that are helpful for early detection of autism, can assist the clinicians and have a key role at the early intervention. Finally, taking into consideration the rapid rhythms of the development of technology, it is worth mentioning that we focused mainly on the researches that were published in the last five years.

2 The Use of Machine Learning

Machine learning is a field of computer science and in particular a branch of artificial intelligence. Its main characteristic is the ability to learn from its past experience by using the previous inputs and improve the new outputs. With machine learning techniques we are able to analyze an enormous amount of data [11]. At a recent study, Stevens et al. identified subgroups of ASD by using machine learning methods

(Gaussian Mixture Models, Hierarchical Agglomerative Clustering). Their purpose was to use these subgroups in order to make personalized interventions. The results of this study prove that machine learning is able to recognize the phenotypes of autism [12]. Heinsfeld et al. investigated the application of deep learning algorithms for the identification of autistic patients based on their brain activation patterns. The database that they used was ABIDE (Autism Brain Imaging Data Exchange) and the accuracy of the algorithms reached 70%. As a result, the high percentage reveals that machine learning methods have a lot to offer and are a very promising tool for the assessment of mental disorders in general [13].

Despite the fact that autism spectrum disorders (ASD) considered being neurological nature, brain biomarkers remain unknown and diagnosis continues to be based on behavioral criteria. With that in mind Chen et al., selected 252 low-motion resting-state functional MRI (rs-fMRI) scans (low head motion) from the Autism Brain Imaging Data Exchange (ABIDE) including typically developing (TD) and ASD participants (n = 126 each), that matched for non-verbal IQ, head motion and age [14]. The results of the study exhibit that while diagnostic classification reached a high accuracy of 91% with random forest (RF), support vector machines in combination with particle swarm optimization and recursive feature elimination performed modestly (with accuracies for validation datasets 70%) [14].

Kosmicki et al. used machine learning in order to study if algorithms can classify the people in two categories, if they belong to the autistic spectrum or not, by using abbreviated characteristics of the ADOS so that the diagnose time is reduced [15]. The results reached 98, 81% of accuracy. Consequently, we observe that these abbreviated classifiers maintain the diagnostic validity of the initial algorithm and if a smaller amount of behaviors are analyzed with machine learning methods they can achieve high percentages of validity at the autism prognosis [15]. Vaishali and Sasikala investigated a machine learning repository using swarm intelligence in order to improve the accuracy and quality of prediction. In their study, they prove that 10 features of the database could possibly make the distinction between the people who belong in the spectrum and the people who don't and the accuracy of this method reached 97, 95% [16].

According to Rad and Furnanello, the majority of the studies were mainly focused on the social and communicational problems of the children with ASD, while the stereotypical motor movement (SMMs) of the patients got less attention. The SMMs are a very important category of the atypical and repeated behaviors of children with autism so it is necessary to develop effective and accurate methods for the automatic detection of these movements [17]. Following this direction, many studies focused on using accelerometer sensors for detecting the stereotypical behaviors of the children with ASD. The accelerometers are electro-mechanic sensors that measure the frequency, the volume and the duration of the physical activity in a specific period. Due to their small size and the possibility to be integrated into mobile phones, the accelerometers are very useful and also appropriate for wearable devices [17].

Another research suggests the classification of the repeated patterns of walking which is based on the kinetic and kinematic characteristics of walking with the help of machine learning [18]. The results of this study suggest that the classification with a linear analysis (LDA) with regard to the kinetic characteristics of walking presented predictions with 82,5% percentage of accuracy and a low percentage of mistake [18].

Mirac et al. [19] examined some prediction factors after a 3-years clinical observation, interventions and psychiatric therapy of a group of children with autism. Specifically, they used machine learning methods to study the psychiatric, developmental, social and demographic elements that affect the prognosis for children with autism. They tried to predict the short term results of autism and discover the clinical and personal factors that affect the improvement of the symptoms. In the beginning, they collected data from control lists like the Autistic Behavior Checklist and the Aberrant Behavior Checklist, which they analyzed with the help of the algorithms Naïve Bayes, Generalized Linear Model, Logistic Regression and Decision Tree. Afterward, they compared the good or poor results according to the frequency of the clinical factors. They chose to use a decision tree to illustrate the data. Even if the results of this study are preliminary, this method can help the clinical doctors to recognize subcategories of patients in autism and also other complex neurodevelopment disorders [19]. Decision trees are trees that are used for classifying instances. Each node of the tree represents a feature of the instant and each branch represents the outcome of that feature. The connective paths represent the classification rules. It is a fact that with the help of decision trees the knowledge can be visualized [20].

Another study classified preschool children with low functioning autism by analyzing with machine learning methods the movements of their upper-limbs. Among 30 children, Crippa et al. investigated if artificial intelligence was able to identify the ones diagnosed with autism just by a kinematic analysis. The experiment involved a simple reach, grasp and drop task with a ball and the mean accuracy reached 84,9%. [21].

Finally, another application that uses machine learning is "Cambridge Mindreading Face-Voice Battery" for adults, which aims at evaluating twenty emotional concepts from video clips with facial expressions and hearing discussions from Mind Reading. After the projection of each video, the participants had to choose between four words that describe better the emotional state of the person in the video clip. From the indicative results emerge that the people with autism, when they are compared with the control group, they present more difficulties in recognizing mental situations and emotions from the video they watched and the discussions they heard [22].

Hence, the purpose of the studies that used machine learning was to make the assessment process of ASD easier and less time-consuming. A big amount of these studies tried to shorten the administration time of ADI-R and ADOS. However, when applying these methods it is crucial to take into account the conceptual and methodological details. For example, it is important that the researchers understand the implications of the validity of the psychometric instrument when it is not administrated entirely. Also, nowadays interdisciplinary methods are necessary. Therefore, the computer scientists who create the algorithms should have adequate knowledge for autism as well as the clinicians should be able to understand the novel technologies. The collaboration of multiple domains appears to be productive in ASD research [23].

3 Neural Networks, Natural Language Processing, and Wearable devices

The main goal of the studies that were involved with artificial intelligence and its applications in the diagnosis of autism was to improve the accuracy of the existed classification scales but, also, to create new scales based on neural networks [24]. Inspired by the human brain the researchers tried to develop algorithms that represent certain levels of intelligence. These are the artificial neural networks which are consisted of an input layer of neurons, one or two hidden layers and one final layer of output neurons. The inputs and outputs from an artificial neural network could be binary or even symbols. They can be very helpful in the data classification [25].

Thomas et al. mention the diagnostic control of autism by using the magnetic tomography of the brain. A region from the structural magnetic tomography is examined for the calculation of the shape of the brain. The structure of the brain of the autistic is expanded and compared with the brain of healthy people. Regarding functional magnetic tomography, the function of the brain is controlled through various tasks. For the final classification, they were used neural networks [26]. Another artificial neural network was created by using the database of the application ASD Tests as well as a database of autism tracking [27]. As input data, they were used ten questions, the age and the sex of the participant. This model predicted autism with 100% accuracy and showed that question number 8 was the one that influenced more the classification.

Another AI field that is used for the diagnosis of autism is Natural Language Processing (NLP). NLP is a domain of computer science focusing on the interactions between computers and human (natural) languages. In particular, it is a way of collecting knowledge on how human beings use and understand language with the purpose of developing appropriate tools and techniques which could make computer systems understand natural languages [28]. NLP uses parts of speech, like nouns and verbs, and grammatical structures. In order to accomplish this, a lexicon of words and a set of grammar rules are integrated into the program [29]. Some of the most commonly researched tasks in NLP are natural language understanding, speech or voice recognition, spelling correction, grammar checking and machine translation [30].

A software that by using NLP can save time from the clinicians and keep a record for the patients is the chatbot. The user gets as feedback written questions or answers that look like the ones that a human would give. The chatbot communicates with the patient using NLP [31]. Every answer that is typed from the user is saved and compared with others (Tokenization). Exactly these saved words form the key to diagnosing the symptom (Keyword extraction). Afterward, the phrases and sentences that the patient used are examined in order to diagnose the severity of the symptom (Similarity matching of the sentence). Consequently, the keywords are examined (Understanding the meaning of Keyword). When all the questions are finished, the symptoms that came as output are also saved and a decision tree gives the result of the diagnosis. Mujeed et al. mention that the accuracy of the chatbot reaches 88%.

Yuan et al. [32] in order to benefit autism patients by enhancing their access to treatments such as early intervention developed a robust system for autism detection by using NLP techniques with machine learning based on information extracted from medical forms of potential ASD patients. The detecting framework involved semi-structured and unstructured medical forms in hand-written format, which were converted later into digital format. Testing results are evaluated by expert clinicians. As a result, the proposed system achieved 83.4% accuracy and 91.1% recall [32].

In addition, another novel technology of AI is WearSense, which utilizes the abilities of modern smartwatches for the detection of stereotypical behaviors in children with autism [33]. It used an integrated accelerometer in order to detect the typical behaviors of people who belong at the autistic spectrum. WearSense technology consists of a smartwatch and a smartphone with an application that collects the sensory data of the accelerometer and also from machine learning algorithms that detect and classify the repeated behaviors. Thus, this technology can help the clinicians at their final decision. The data that came as an output and the decision trees that were used had 96,7% accuracy at the detection of the autistic behaviors [33].

4 Fuzzy Logic Techniques

Fuzzy Logic (FL) is based on the observation that people make decisions based on imprecise and non-numerical information. Briefly, it is a computing technique for the calculation of the "degrees of truth". Fuzzy Logic includes 0 and 1 as extreme cases of truth, (where 0 represents “totally false”, 1 represents “totally true”) but also includes the various states of truth in between (where the other numbers refer to partial truth) [34]. Fuzzy logic uses fuzzy rules which form the key tool for the expression of knowledge. Yet, there is a diversity of fuzzy rules as well as in fuzzy logic itself [35].

The previous studies focused on detecting single disorders while, at a recent study, Kaur and Kakkar investigated a new platform that uses fuzzy logic and predicts the co-morbidity of ASD (Autism Spectrum Disorder), ADHD (Attention Deficit Hyperactivity Disorder and ID (Intellectual Disability) [8]. The main concern was that these disorders have many characteristics in common, which makes the diagnose process even harder. Kaur and Kakkar presented a Fuzzy Rule-Based System (FRB) that analyzes the symptoms of the patients and the results that are exported mention if a patient is Typically Developing (TD) or if he belongs to one or more categories of the above disorders, indicating at the same time the severity of each disorder [8].

Nguyen and Ngo at their research suggest a combination of neural networks and fuzzy logic for the early diagnosis of autism [24]. Since the artificial neural networks demand a big amount of samples and due to the difficulty to find real data, they decided to use a temporary database that was created for CARS (Childhood Autism Rating Scale). For the relationship of the child with people, four levels were created that show the level of relevance with autism [24]. Level number 1 states that there are not elements of difficulty with the relationship with others, level number 2 that the relationships of the child are slightly dysfunctional, level number 3 that the relationships are relatively dysfunctional while level number 4 states seriously dysfunctional relationships. According to Nguyen and Ngo, the combination of neural networks with fuzzy logic had a 95,79% success. Pratap et al. [36] described a fuzzy model which uses if-then rules and automatically classifies the children in 4 categories (normal, mild, moderate and severe) according to how much a symptom contributes to the overall severity. This method has higher percentages of accuracy than the traditional ways of assessment

In parallel, if we combine the properties of fuzzy logic and neural networks we will have Fuzzy Cognitive Maps (FCM), which constitute a tool to represent knowledge and also form an effective method of AI for the development of complex systems [37]. Puerto, Aquilar, Lopez, and Chavez suggest a computational model that uses Multilayer Fuzzy Cognitive Maps (MFCM) based on standardized methods of autism diagnosis. To be more specific, the two standardized models that were used were ADOS2 and ADIR. The properties of MFCMs are so augmented that allow the characterization of different forms of autism. Analytically, the inputs represent the symptoms and the signs of autism while the outputs represent the severity level of the symptoms. For example, the final output of OUTADIR represents the presence (or absence) of autism. This classification is given when the results of at least two from the three outputs of the system meet or exceed the special limits [37]. The researchers compared their model with classical algorithms of classification, selecting their sample randomly (almost 50% of the children had an autism diagnosis) and they found that MFCM-ASD at this database had 83% of success.

5 Artificial Intelligence and Mobile Applications

Guimares et al. developed a mobile application that could help the detection of autistic features. [38]. The system that is based on the app uses artificial neural networks and fuzzy systems trained by learning machine algorithms to generate fuzzy rules to deal with questions provided by users seeking to obtain immediate answers on preliminary diagnoses of autism in adults. A sample of 701 participants was tested with age 17 plus. The results of the tests exhibit that the mobile application can be a useful tool for the diagnosis of autism in adults as it performed high levels of accuracy, between 95.85% and 95.73% [38].

Another study that reduces the time and cost of ASD diagnosis is the ASDTests application by Alisson et al. [6]. This application offers friendly, easy-to-access and time-efficient tests that are available to a wide range of users from infants to adults and in 11 languages. An additional feature of this application is the collection of data for further research. After 4 months of use of the ASDTests application, 1452 incidents had been collected. All incidents were evaluated by machine learning algorithms to highlight those features that maximize the predictive precision of autism classification and reduce the processing time of the data. According to the results, self-administered and independent applications such as ASDTests, with a short-version questionnaire, enhance the degree of efficiency and accuracy [6].

Duda et al. created the Mobile Autism Risk Assessment (MARA), a screening tool for parents and guardians, which is a five minutes tool delivered through an online platform with automatic results display. MARA is a 7-item questionnaire about the social and communicational skills and behavior of the child [39]. Each question is accompanied by 4-5 possible answers but also by the option "not applicable". Answers are processed by a machine learning model that uses a decision tree algorithm that in turn produces the result. The sensitivity of the MARA in detecting ASD was 89.86%. All in all, this study demonstrates that MARA is a promising screening tool to distinguish ASD from other developmental/behavioral disorders [39].

Kanne, Carpenter, and Warre presented a new evaluation tool, a mobile phone application that covers a wide range of ages and potentially increases accuracy due to its innovative approach. This tool is called Cognoa and it is designed to evaluate the risk of autism between general and high-risk populations. It includes the ages of 18 months to 5 years. In the first phase, the parent needs to complete a 15 multiple answers questionnaire [40]. Questions are designed to examine the same features as Autism Diagnostic Interview-Revised. A machine learning algorithm is conducted in the parent's questionnaire and produces 4 risk categories (low, moderate-not autism, moderate, elevated). In the second phase, parents are asked to record up to four, 1–2-minutes videos in different scenes of everyday life. When the videos are rated by analysts, a different algorithm is performed to produce the same four risk categories. The classification tool generates a quantitative degree that attempts to outline the autism severity phenotype, which is transformed into categorical risk descriptions such as "low" or "increased" risk. The results of the study suggested that Cognoa has the abilities of a psychometric tool as it accurately identified 71% of the cases [40].

Tariq et al. attempted to lower the waiting hours, increase the number of cases under consideration, and the percentage of accuracy, validity, and reliability by creating an online platform with machine learning's aid, which would evaluate videos taken home by mobile phones [7]. Also, Mamun et al. [41] presented the Smart Autism application which follows three stages during the export of results:

- Screening
- Virtual Assessment
- Actual Assessment

Particularly it contains a platform in which a child's details are imported and based on its age the application selects the appropriate method of detecting the disorder. Then, groups of interactive questionnaires with images, animations and videos are demonstrated. After the user answers the questions, the results are analyzed and the corresponding result is displayed. If the detection results are positive, then the app projects to the child with a rating video and records the child's reaction and expressions (virtual assessment) with camera help. Then the experts study the video and if they consider it necessary, they refer the child to a medical center that can be diagnosed with autism (actual assessment).

Additionally, a new method that is called Rules-Machine Learning detects autistic characteristics but also offers the users basic knowledge (rules) which can be used by the specialists during classification. Indeed, empirically results from data collection from children, teenagers and adults prove that this method offers classifiers with higher predictive accuracy and specialization than other machine learning methods like boosting, bagging and rule induction. Particularly, the data are collected from the application ASDTest with four different selection methods. Afterward, the group of data is evaluated and the result of this evaluation is used for the prediction of the category that each person belongs [42].

7 Conclusion

In conclusion, artificial intelligence is increasingly being studied in relation to the positive effects it can possibly have on the assessment of autism. Machine learning, fuzzy logic, natural language processing, neural networks, and mobile applications have a lot to offer at the diagnosis of autism and other neurodevelopmental disorders. As a result, in this article, we focused on presenting briefly the significant role that artificial intelligence plays at the early detection of autism and how the use of new technologies helps families, clinicians, and children with the tiring and long evaluation process. For instance, the waiting time for evaluation can be reduced. Furthermore, AI gives the opportunity for processing and classifying a bigger amount of data. In addition, according to the results of the studies, the percentages of success and accuracy of the applications are very high. Hence, they can be helpful in the diagnose process by aiding the clinician to make safer decisions and acquire a better image for the capabilities and the needs of the child. Also, diagnose is based on the characteristics of each child and can be realized in a short period. Finally, by using artificial intelligence applications the cost for the assessment can be reduced. It is worth mentioning that these applications can also be accessible by families with children who present autistic symptoms and become the basis of the diagnosis. Besides, the main goal is the early detection of the disorder so that people with autism get a proper intervention, be included and feel equal and useful members of our society. Therefore, it is important to continue the research on this topic in order to develop innovative methods that make the diagnose process easier, faster, more accurate and less expensive.

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