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Applying Artificial Intelligence in Diagnosis and Treatment of Autism Spectrum Disorder in Children

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ABSTRACT

Autism Spectrum Disorder (ASD) is a disorder of increasing prevalence that affects individuals socially, emotionally, and academically. The increased prevalence and restricted access to diagnosis and treatment suggest more efficient and widely accessible services are necessary. Many individuals with ASD do not receive proper attention due to various reasons, including costs, long wait lists, and long processes. Recent developments in artificial intelligence and machine learning are believed to be able to aid this accessibility issue. Research has shown progress in using MRI and EEG datasets to develop machine learning models in diagnosing ASD and potentially finding biomarkers using supervised and unsupervised ML techniques. AI algorithms analyzing body language and physical behaviors could potentially be used to assess ASD characteristics despite the heterogeneity of the disorder. The adaptivity of artificial intelligence is believed to have the potential to create supportive software for students with ASD to support learning, emotional regulation, and development of social communication skills and increased adaptability. More evidence is required to prove the effectiveness of these applications, but many studies show a lot of promise for children with ASD.

Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder characterized by a broad range of conditions, including challenges with social skills, communication difficulties, and struggles with rigidity and restrictive attitudes [1]. These conditions manifest in behaviors such as repetitive tendencies and issues speaking at appropriate volumes, with appropriate physical distance, and interpreting gestures and facial expressions [2]. According to the Centers of Diseases Control and Prevention (CDC) , as of 2023, among US children aged 3-17 years, about 1 in 36 children, or 2.8% have been identified with ASD [2]. The presenting symptoms of autism vary depending on age, but in children, a common negative effect is slower development and hindering their progress academically and socially compared to normal children [3]. Additionally, co-occurring developmental and psychiatric conditions are common in children with ASD, including a higher risk of Attention-deficit hyperactivity disorder (ADHD), anxiety and depressive disorders, and increased risk of medical conditions such as epilepsy, gastrointestinal conditions, and sleep difficulties [4]. Indirect and direct costs of an autistic child are, on average, $1.4 million for those without intellectual disability to $2.4 million with intellectual disability [5,7].

Because ASD encompasses a wide range of symptoms and behaviors, it is difficult to diagnose, especially in its milder forms or in individuals with co-occurring conditions. Additionally, manifestations of ASD are heterogeneous and include a wide spectrum of individuals [6]. ASD diagnosis is an expensive and time-consuming service, and families often have to wait on long waitlists to be seen by a professional [10]. Many often go undiagnosed until adulthood. Individuals may also be misdiagnosed early before ASD, with conditions such as ADHD, obsessive-compulsive disorder (OCD), or social anxiety disorder (SAD). Early diagnosis is crucial because it allows for early intervention and support for the child and family. Later diagnosis can lead to greater mental health difficulties [8]. People diagnosed with autism in adulthood are nearly three times as likely as their childhood-diagnosed counterparts to report having psychiatric conditions [9].

After diagnosis of autism, interventions are necessary to improve an individual's function and well-being. While no medications have proven effective at alleviating core characteristics of ASD, psychological and behavioral interventions such as talk therapies (CBT), and attaining behavior change to improve symptoms of ASD rather than features is shown to positively improve wellbeing [1]. However, interventions are expensive and are not accessible to all. In a school setting, children are often not given the proper specialized education they need and they face risks of falling behind. Higher proportions of autistic students do not graduate high school with a diploma (26.4% of students with autism compared to 14% of students without autism). Furthermore, there is a shortage of trained professionals that limits the availability of services for many, and the financial burden may prevent families from seeking care [10].

Artificial Intelligence (AI) refers to computer systems capable of performing tasks that typically require human intelligence. Its subset, Machine Learning (ML), focuses on developing algorithms and models that can make predictions or decisions based on data with or without instructions from human beings and improve themselves by learning from computational experience over time. AI/ML has been widely used to identify brain conditions such as Alzheimer's disease, dementia, schizophrenia, multiple sclerosis, cancer, and infectious and degenerative diseases using available unstructured data such as Medical Imaging and genomic information to predict, study, treat, and manage mentioned conditions [11]. Deep Learning (DL) is a subset of ML that teaches computers to function and process like the human brain. The usage of AI/ML/DL in the identification of mental disorders has increased rapidly in recent years.

This review aims to discuss applications of artificial intelligence in the diagnosis and treatment of Autism Spectrum Disorder in children.

Diagnosis

Magnetic Resonance Imaging (MRI) allows for the non-invasive study of brain activity. Functional MRI (fMRI) is a technique that measures brain activity by detecting changes associated with blood flow, while structural MRI (sMRI) maps brain structures and provides sequences of contrast in brain tissue. MRI has been widely used since the 1990s to collect data and make inferences for patients with mental disorders [12]. Research has demonstrated the efficacy of using ML methods to analyze MRI datasets. Using raw data, images are classified with ML and DL models that are exempt from typical subjectivity by doctors to realize patterns that can provide auxiliary diagnosis along with typical processes [13]. Supervised learning is a ML method that defines a desired output to train a model, in contrast to unsupervised learning, which receives unlabeled data and discovers patterns without any guidance of output features [14]. Support vector machines (SVMs) and Random forests are supervised learning methods commonly used for classification, regression and outlier detection [18].

sMRI data provides information on features that characterize brain structure and function, such as measures of cortical thickness, volume of certain brain regions, or functional connectivity between different brain regions. fMRI data provides information on correlation coefficients between time courses of different brain regions [15]. Based on data from the National Database for Autism Research (NDAR), Dekhil et al. found 75% classification accuracy using fMRI data only, 79% classification accuracy using sMRI data only, and 81% using both features [15]. With sMRI data and fMRI data combined, Random forest outputted an 81% classification accuracy and SVM had a 71% classification accuracy [15]. Other applications of SVM on sMRI vary, with accuracy rates ranging from 45 to 94% on various ASD datasets [20]. According to Liu et al., applying different machine learning methods and fMRI data acquired from different sites, classification accuracies were obtained ranging from 48.3% up to 97% [21].

Physical identifiers of ASD have been potentially seen as abnormalities in frontal, parietal, and limbic regions, as well as the basal ganglia and the cerebellum, though differences are highly variable and typically unreliable due to the heterogeneous nature of the disorder [16]. Variability in studies indicates subtle differences in brain anatomy, and indicators of ASD in the brain are not confined to a single morphological parameter but affect multiple cortical features [17]. Ecker et al. proposed a model based on volumetric and geometric features at each spatial location on the cortical surface to discriminate between individuals with or without ASD. Their volumetric and geometric features included average convexity or concavity of the folding pattern of the cortical surface, mean radial curvature, metric distortion indicating the degree of cortical folding, cortical thickness, and pial area to measure brain volume. This study applied an SVM to differentiate patient groups and control groups with an accuracy rate of 85% [17]. Resting-state functional connectivity (FC) measures were proved to be potential diagnostic biomarkers for ASD in potentially identifying an ASD biomarker. Zhao et al. proposed that the high-order FC could be affected in ASD compared with the traditional FC and, therefore, can be used as effective biomarkers for ASD diagnosis [22]. However, work in identifying an ASD biomarker is still being done [21].

The development of the Autism Brain Imaging Data Exchange (ABIDE) database has greatly facilitated the development of machine learning models for the automated diagnosis of ASD. A study by Parikh et al. used personal characteristic data (PCD), specifically age, sex, handedness, and three individual measures of IQ from the ABIDE database. Out of the models tested, including decision tree, majority model, random forest, linear and nonlinear SVM, confidence model, logistic regression, k-nearest neighbor, and neural network, both linear and nonlinear SVM had the highest efficacy rates in terms of accuracy, sensitivity, specificity, and cost-effectiveness. The purpose of this study was to demonstrate the predictive power of PCD, which was 61% accuracy [19].

Electroencephalogram (EEG) is a non-invasive recording of brain activity widely used due to its mass availability and cost effectiveness [23]. Though unreliable when solely assessed by humans, various studies have applied ML techniques to attempt to diagnose ASD using EEG readings with various accuracy rates. Tawhid et al. find that DL-based structures can be used to discover important biomarkers for efficient and automatic diagnosis of ASD from EEG and assist with computer-aided diagnosis. Their DL model found 99.15% accuracy [24]. Bosl et al. again found that useful digital biomarkers might be extracted from EEG measurements. Their predictions of diagnostic outcomes of individuals of up to 3 months of age were shown to be very accurate and were also able to predict symptom severity. Early detection of emerging ASD using these models was classified with high accuracy [25]. Though there are more studies of EEG-based diagnoses, they are unfortunately often limited by small study sizes. Additionally, EEG-based studies typically use higher proportions of male subjects, leading to a skewed representation of female subjects with ASD, which questions the validity of results [26].

Studies done by researchers at the University of Geneva have developed an algorithm that uses artificial intelligence to analyze the movements of a child to identify potential characteristics of ASD. The basis of their algorithm involved 68 typically developing children and 68 children with autism. Their model achieved an accuracy of 80.9%, with the prediction probability positively correlated to the level of symptoms of autism demonstrated per subject. The study assessed 27 individual traits, including gestures, immediate echolalia, the intonation of vocalizations or verbalizations, pointing, stereotyped language, use of another's body, frequency of spontaneous vocalizations, facial expressions directed to others, giving, IJA-initiation of joint attention, integration of gaze and other behaviors during social overtures, response to name, quality of the relation, quality of social response, quality of social overtures (SO), requesting, RJA-response to joint attention, shared enjoyment in interaction, showing, unusual eye contact, functional play with objects, imagination, unusual sensory interest in play material/person, hand and finger and other complex mannerisms, self-injurious behaviors, unusually repetitive interests or stereotyped behaviors. However, the limitation of this study is the broad nature of autistic traits and behaviors. ASD cannot be detected solely based on singular behavioral acts and is also characterized by impairments that may not manifest in physical traits [27].

Treatment

Treatments of ASD utilizing AI/ML methods are usually extra support systems based on proven techniques to support autistic individuals. This includes methods of emotional regulation, individualized education services, and behavioral interventions [1]. Researchers have made progress in using emotion recognition to detect negative emotions and adaptive learning systems to help students with ASD deal with social conflict situations [29].

Children with ASD show clinically significant emotional difficulties and impaired cognitive flexibility that leads to more frustration than neurotypical peers that inhibit learning. Approximately 74% of children with ASD have significant emotional difficulties compared to 18% of typically developing children [30]. E-learning systems offering emotional assistance require automatic emotion recognition and adaptive emotional regulation [29]. Several machine learning methods are used by researchers, most frequently SVMs and artificial neural networks. Observable characteristics to detect emotion shifts include but are not limited to movements in facial expression, body posture, eye gaze, gestures, heart activity, muscle tension, perspiration, and brain activity [28]. Adaptive emotional recognition techniques can be applied to detect students' negative emotions, such as frustration, anxiety, and resignation.

Chu et al. proposed a plan where new students took a pre-test to predict the learning style, and their model was used to plan tentative learning paths that were adaptive per student. It is important that the path does not discourage students from continuing and reduces frustration. Students follow the learning path, possibly requiring remedial learning to support students. In this study, students' affective states were assessed to spot negative emotions and apply regulation strategies. The emotional regulation portion of the proposal is based on James Gross' emotional regulation process. Gross outlines five steps: situation selection, situation modification, attentional deployment, cognitive changes, and response modulation [31]. The proposal divides emotional regulation strategies into 3 sections: response modulation, cognitive change, and attention deployment. Response modulation includes a computer-aided adaptive program instructing students on modifying responses to stressors using techniques like muscle relaxation, deep breathing, and positive imagery. Cognitive change entails computer-selected strategies, including social stories, self-instruction, and self-management. Each strategy is aided by video and audio instructions. Attentional deployment helps direct the individual's attention toward positive aspects of the situation while focusing attention away from negative aspects. This includes educational games and graphic animations. This model used SVM to construct the emotion recognition model with an overall recognition rate of 93.34% accuracy. The implementation of the model was shown to greatly improve the efficiency of learning, performance per student, and reduction of negative emotions. The preliminary results of the study suggest that a larger trial is needed to confirm the efficacy of the proposed model [29].

Augmented reality (AR) as a therapy method has been shown to have positive results when used in combination with cognitive behavioral therapy (CBT) for mental illnesses. AR glasses and headsets used as classroom-assisted learning tools have improved the irritability and rigid behaviors of children with ASD [32]. AR shows advantages over traditional interventions as it allows for more realistic environments that are adaptable to the very heterogeneous characteristics of ASD in children. Research shows that children with ASD and parents positively react to AR-assisted learning. AR assistance has been shown to improve social interactions and recognition of verbal and nonverbal cues, among other features of ASD [33]. AR techniques could be an effective supplement to traditional cognitive/behavioral interventions for children with ASD.

Conclusion

ASD is a complex and heterogeneous disorder with no single method of diagnosis or treatment. Due to this, it requires well-developed and expansive methods of detection with the variability of the condition in mind. There is certainly promise in incorporating AI/ML methods in the diagnosis and treatment of ASD. Developments of

ML/DL models to diagnose ASD demonstrate accuracy and specificity in literature. However, many are limited by small sample sizes and require further testing to confirm usability. Despite this, there is potential for refinement and finding an ASD biomarker and increasing accessibility and efficiency of ASD diagnosis. Treating ASD using adaptive learning and emotional regulation techniques and augmented reality also requires further research. The relationship between ASD and AI has gained significance only recently, underscoring the imperative for additional evidence to bolster these models, particularly given the diverse nature of the condition.

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