Chapter 1
Computational Intelligence in Detection and Support of Autism Spectrum Disorder

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Abstract Autism Spectrum Disorder (ASD) refers to a spectrum of conditions characterised mainly by impairments in social interaction, speech and nonverbal communication, and restricted - repetitive behaviour. The lack of physical testing, done primarily via behaviour analysis, makes ASD diagnosis more difficult. The emergence of Computational Intelligence techniques has resulted in the development of a variety of fast and early ASD diagnosis methods based on multiple input modalities. The premise of computational intelligence (CI) and its efficiency in detecting and monitoring ASD has been examined in this chapter, which has recently advanced. Two types of studies have been discussed in this article. Several aspects of ASD screening, including questionnaires, eye scan paths, movement tracking, behavioural analysis from video, brain scans, and more, have been discussed using machine learning and deep learning. Secondly, ASD detection and monitoring applications have been studied extensively in the past year, with significant advances.

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Finally, a discussion has been made on the challenges faced in ASD detection and management with future research scopes.

1.1 Introduction

Autism spectrum disorder (ASD) is a complicated, irreversible developmental condition that usually manifests in early infancy and negatively influences a person's social skills, communication, relationships, and self-control. According to the fifth edition of the diagnostic and statistical manual of mental disorders [1], ASD is a neurodevelopmental disease characterised by deficits in social communication as well as the occurrence of repetitive and restricted patterns of activities, behaviour, or interests. Deficits in social-emotional reciprocity, nonverbal communicative behaviours during social interactions, and difficulty in developing, maintaining, and understanding relationships are the primary indicators of impairments in social communication. Some of the signs that manifest restricted and repetitive patterns of behaviour and activities in people with ASD include stereotyped or repetitive motor movements, insistence on sameness, inflexible adherence to routines, ritualised verbal or nonverbal behavioural patterns, hyper- or hypo-reactivity to sensory inputs, and unusual interest in sensory aspects of the environment. These signs have been used in identifying the varieties of ASD. Faras et al. [2] have termed ASD as a Pervasive Developmental Disorder (PDD) and categorised to: Autistic Disorders (AD), Asperger's Syndrome (AS), Childhood Disintegrative Disorder (CDD), Pervasive Developmental Disorder-Not Otherwise Specified (PDD-NOS) and Rett Syndrome (RS).

A clinical study suggests that toddlers who got early intensive therapy not only had functional gains but also required fewer services than those who received "treatment as usual" during a two to three-year follow-up period, which resulted in overall cost savings [3]. As a result, early intervention—and, by implication, early diagnosis—have the potential to enhance function while lowering societal costs [4]. Early identification of children with impairments and their treatment has been found to improve child outcomes for the developmental disorder (DD), and autism [5]. Developmental monitoring (also known as developmental surveillance by the American Academy of Pediatrics) is promoted by the World Health Organization [6] as a procedure for the early diagnosis of developmental difficulties, particularly in low, and middle-income countries (LMIC). In comparison to relying solely on clinical diagnosis, evidence from high-income countries (HIC) suggests that providing screening instruments in routine healthcare visits can result in earlier and more accurate identification of children in need [7]. Regular screening for ASD or DD during healthcare visits is an effective way to detect the condition early and allows any referral for additional diagnosis and intervention. Despite its significance, however, early diagnosis remains a hurdle in both HIC and LMIC [8]. In early life, when developmental changes are fast, early symptoms are typically subtle, and this makes the identification difficult [9]. In general, ASD diagnosis is a complex procedure due to the disorder's developmental and widespread nature. Many of the signs of ASD, such as delayed expressive language development, poor social responsiveness, behavioural issues, and repetitive behaviour, can also be found in other disorders and syndromes. The presence of intellectual disabilities further complicates the differential diagnosis process, especially in very young children whose impairments in interpersonal interactions must be separated from the ones produced by other cognitive impairments. Professionals use a variety of official and informal ASD screening techniques. These might be anything from casual observations to official evaluations.

The Modified Checklist for Autism in Children, Revised (M-CHAT) is a common 20-question assessment designed for children aged 16 to 30 months [10]. The Ages and Stages Questionnaire (ASQ) [11] is a broad developmental screening method that focuses on developmental issues at distinctive ages. The ASQ consists of 40 questions on reciprocal social interaction (such as social smiling, willingness to participate with other children, and trying to offer comfort to others), language and communication (including the use of traditional gestures, interpersonal conversation, and generalising utterances), and repetitive and stereotyped behavioural patterns. The ASQ also contains a question concerning self-injurious conduct and another about the individual's present language functioning [11]. Autism Diagnostic Observation Schedule (ADOS) contains semi-structured observational questions. The examiner assesses the child's answers to various familiar and unusual circumstances, looking for ASD-related behaviours. ADOS consists of several subtasks whose goal is to determine social capabilities, such as eye contact and social smiling [12]. Autism Diagnostic Interview, Revised (ADI-R) is a semi-structured questionnaire for family caregivers to diagnose ASD by interpreting parents' observations about their children's everyday activities [13]. Because the ADI-R evaluation depends on caregiver reports, it does not allow for direct observation of children's social behaviours. Instead of relying solely on psychoanalysis or other theoretical assumptions, Childhood Autism Rating Scale (CARS) is based on direct behavioural observation. The CARS is beneficial for research and administrative classification and for generating a comprehensive explanation of a child's unusual behaviour [14]. The following are some popular techniques for controlling and monitoring ASD systems: at the outset, ASD symptoms must be discovered, which may be done in various ways, such as utilising questionnaires to identify the most prevalent ASD signals. Once this step is complete, we may use the Internet of Things (IoT)-based devices that use different sensors to track an individual's everyday actions. We can monitor individuals' behaviour and how they respond to diverse circumstances by deploying these technologies. After identifying it, we can develop a system to monitor or ease their behavioural cycle. We can utilise a variety of apps or web-based platforms to do it. Thus, we can train them and improve their lives by providing diverse approaches, equipment, and other resources.

1.2 Computational Intelligence

Computational intelligence (CI) as a domain aims in creating intelligent systems to solve complicated problems. In real-life optimisation, classification, or regression problems, all the possible states or outcomes are too large to compute using the most sophisticated computer systems. The scarcity of deterministic methods has led to the development of nature-inspired methods to find valuable solutions and heuristics from uncertain, incomplete databases. These methods, also driven by utilising learning methods from experiments and data, can provide approximate solutions for many NP-hard problems using fewer computations and resources. Thus CI refers to utilising learning methods from experiments and data [15]. The main key point for CI algorithms is the trade-off between accuracy and computational time. Again using learning parameters that are set as constants for these algorithms allows leading to the desired solution more quickly.

The scope of CI is quite vast and includes fuzzy computing, neural networks, and evolutionary computing. Over time, these learning methods evolved, and machine learning and neural networks have received extensive attention lately. A vast amount of methodology has been derived from these branches. According to Kruse et al., CI consists of neural networks, fuzzy logic, evolutionary algorithms, and Bayes networks [16]. Swarm intelligence is also mentioned as a core part of CI by Engelbrecht et al. [15]. In terms of applications, techniques pertaining to these diverse areas have been applied in a wide range of problem domains including anomaly detection [17, 18, 19, 20, 21, 22], disease detection [23, 24, 25, 26, 27, 28, 29, 30, 31] and smart data analytics [32, 33, 34, 35, 36, 37, 38, 39, 40].

1.2.1 Neural Networks

Neural networks are inspired by the learning methods of our brain, and by simulating the brain's functioning, computers can learn and process various heuristics. This is mainly done by creating artificial neurons and connecting them so that they can mimic the brain's functioning. At the artificial level, each neuron responds conditionally to convey some information or not. When many such artificial neurons are connected, they create a network for learning subtle patterns that solve complex problems. Until recently, putting together a large neuronal network and making them learn required significant computational. However, currently, it is possible to experiment with deeper structures of such Artificial Neural Networks (ANN) due to the recent advancements in hardware technologies and programming libraries [41]. Common examples of such large scale artificial neural networks include Convolutional Neural Networks (CNN) for image classification and processing, recurrent neural networks and Long Short Term Memory (LSTM) for analysing time-series data, and Generative Adversarial Networks (GAN) for synthetic data generation. Modern trends towards self-supervised learning, federated learning, and deep reinforcement learning are also increasing.

1.2.2 Fuzzy Logic

Fuzzy logic has been attributed to human decision-making, which takes advantage of our ability to reason with relatively incomplete or approximate data [42]. Instead of placing true or false conditioning, the approach utilises a continuous rating for making decisions. Thus it works well with partial reasoning and tries to duplicate human cognition. This approach of intermediate truth allows a fuzzy set to contain a wide range of values between 0 and 1. These properties made fuzzy logic ideal for scenarios with incomplete and imprecise data, such as natural language processing or control engineering. Exploiting this approach of low power computation, many modern systems like temperature controlling, washing machines, and gear selection in automobiles utilised fuzzy logic. Fuzzy logic is based on the if-then rule, variables and membership functions. The fuzzy membership functions are employed to transform the initial raw input supplied to a fuzzy system. Fuzzy logic does not work on its own; instead, it describes the relationship of the If-then rules using the membership function. A rudimentary fuzzy system could categorise input data before applying if-then rules to different continuous variables with predefined ranges. The initial if-then description is applied as if some variable has a specific range of values, then the variable changes. However, this type of initial logic is given by humans and may contain errors, imprecision and false data. Hence, fuzzy logic allows comprehension in an unconventional environment to better understand the relevance of the insights.

1.2.3 Evolutionary Computation

Evolutionary computation is a discipline of soft computing and AI that consists of optimisation algorithms based on biologically inspired methods. Overall, in the techniques, stochastic optimisation is achieved through the nature-inspired population using trial and error methods [43]. By replicating the behaviour of natural elements, evolution or mathematical changes occur on a step by step basis. A preliminary collection of possible solutions is developed and continually revised for an optimal solution in evolutionary computing. In each iteration, lesser desirable information is stochastically discarded through randomised modifications. An explicit fitness function is used to compute the necessary statistical correctness of each solution. Nature-inspired selection criteria are then applied to a set of possible solutions toward finding the optimised solution. Again these solutions work as the base for the subsequent iterations. Hence a sub-optimal solution is reached with relatively less computational power.

1.3 Computational Intelligence in Autism Detection

Various sensing technology embedded within wearable devices, such as microphones, heart rate, motion, accelerometer, and pulse oximeter, provide a better insight into the ailments and symptoms of a patient. Similarly, video, simulation, eye tracking, and virtual reality-based scenarios contribute to the accurate assessment of ASD diagnosis rather than the questionnaire-based ones [44]. These devices can collect critical patient information, which then can be analysed using machine learning (ML) and deep learning (DL) algorithms to extract relevant information [45, 46, 47, 24, 48, 49]. Initial diagnosis of ASD based on data from IoT devices might perhaps assist professionals. Moreover, IoT and ML systems allow for mass primary diagnosis with little or no health professional involvement. Therefore, the datasets play an essential role in the diagnosis of ASD.

1.3.1 Datasets and Methods

Many researchers have conducted studies with different modalities of data to identify biomarkers and traits among ASD and neurotypical people. Multiple studies in the literature have reported various data acquisition techniques to find differences in biomarkers among ASD, neurodegenerative and neurotypical patients. Labelling these key biomarker-based features in each dataset provides future research scope for researchers of different backgrounds. Since creating a dataset is a tedious task requiring multidisciplinary contribution, several datasets have been made publicly available, covering a range of modalities from structured data to image, audio, and video data.

The ASD screening in children dataset consists of a total of 20 features(10 behavioural features and 10 individual characteristics) that are utilised to classify ASD cases [50]. A further innovative way of ASD detection using the Scanpath Trend Analysis is the use of eye movement from the web [51]. An eye-tracking dataset featuring visualisations of eye-tracking Scanpaths focusing on ASD allows identifying the condition from eye-movements [52]. Carette et al. [53] proposed an eye movement tracking based ASD detection system using LSTM. A total of 17 ASD and 15 neurotypical patients were studied with an accuracy of 83%. Elbattah et al. [54] suggested an eye-tracking Scanpath method for ASD classification using the K-mean clustering algorithm and reported maximum accuracy with the k value set at four. Similarly, Carette et al. [55] presented a technique that converts an eye-tracking Scanpath into an image and then classifies the image for ASD screening. They experimented with Random Forest (RF), Support Vector Machine (SVM), Linear Regression (LR), Naïve Bayes (NB), and ANN algorithms and obtained a maximum AUC of 90%. Tao et al. [56] classified ASD utilising eye Scanpath using saliency mapping from Convolutional Neural Network (CNN) generator and discriminator part with encoder, decoder. An image has been given to the patient to capture their eye Scanpath, then utilising a CNN-LSTM algorithm for classification. In an interesting review work, Chita-Tegmark et al. [57] reviewed 38 eye-tracking and eye Scanpath based ASD detection methods. They considered eight factors to measure the effectiveness of each method.

Data were collected using a mobile app called ASDTests to form another structured dataset to test autism in toddlers [58]. In addition, datasets consisting of 300 images from 28 individuals with and without ASD [59] and video clips of children with ASD performing reach-to-grasp activities [60] have also been reported.

Goal et al. [61] proposed a modified Grasshopper Optimisation Algorithm (GOA) for feature selection in the AQ10 questionnaire-based data set, which improved the classification accuracy of RF, LR, NB and KNN and achieved 100% accuracy for child and adolescence datasets. In another work, Pratama et al. [62] applied SVM, RF, and ANN on the AQ10 dataset with 10-fold cross-validation without any feature selection. Thabtah and Peebles [63] proposed a new rule-based architecture for detecting ASD on several ASD datasets. During this, the bagging, rule induction, boosting, and decision trees methods were empirically assessed, with RML outperforming the others. Kupper et al. [64] prepared an ADOS questionnaire and conducted a survey in Germany. They minimised the feature of ADOS into only five attributes. Then classification was applied using SVM with an AUC of 82%. Levy et al. [65] proposed techniques to extract features from the ADOS questionnaire and applied 17 different supervised learning models. Their extracted feature set also contained information related to sex and age and could differentiate ASD from non-ASD reliably. The ML techniques include LR, Lasso, SVM, ADTree, RF, Ridge, Elastic net, LDA, AdaBoost, etc.

Oh et al. [66] proposed an EEG based ASD detection system where they used Marginal Fisher Analysis and Student's t-test for selecting features that were classified using an SVM classifier. Data from 37 children were classified with an accuracy of 98%. Similar EEG-based classification using transfer learning and pre-trained models were used by Bygin et al. [67]. For feature extraction, they used local binary pattern and short-term Fourier transform. The features were transformed into image format for classification. Khodatars et al. [68] reviewed deep learning-based methods suitable for neuroimaging-based diagnosis and rehabilitation of ASD. Challenges related to ASD detection and management were also addressed in this article. Classifiers such as SVM and K-means have also been utilised for ASD detection. Parvathi et al. [69] categorised children below three years old with ASD and achieved 96% accuracy using SVM. In another work, Jagota et al. [70] applied an ANN-based approach to detect ASD patients. Structural Magnetic Resonance Imaging (sMRI) has also been utilised to analyse the brain functionality of ASD patients. To classify ASD Mishra et al. [71] extracted surface and volumetric morphometric features of sMRI to classify with SVM, RF, K-Nearest Neighbours (KNN), and Extra Trees (ET) ML models. They also provided a comparative analysis for each of the ML classifiers. Raj et al. [72] used three publicly accessible datasets to compare the performances of LR, SVM, NN, NB, and CNN.

Rule-based ML methods have also been applied to ASD screening to provide more insight into the models' decision-making process to the clinical experts. Thabtah et al. [73] devised and evaluated such approaches on datasets from adults, adolescents, and toddlers. Omar et al. [74] merged classification and regression tree-random forest (RF-CART) with RF-ID3 and implemented it in a mobile app. Hossain et al. [75] examined 25 machine learning classifiers on a collected ASD dataset and found that SVM based on Sequential minimum optimisation (SMO) performs best in their experiment setting. Though individual screening systems like questionnaires, eye tracking, neuroimaging, genetic data, and electronic health records provide adequate results, the combination of these methods yields greater accuracy. A multimodal screening system consists of each screening method, as mentioned earlier, and then summarises each prediction into a final prediction. Multiple ML classifiers run parallelly with a final classifier that takes each of the first stage classifiers as input. In this manner, several ASD symptoms can be analysed for diagnosis [76].

1.4 Computational Intelligence in Autism Management

Since ASD is correlated to physiological changes associated with negative emotions in people, monitoring these emotional changes can provide caregivers with a real-time picture of what these people are going through. An effective monitoring system may raise caregivers' awareness of a person's emotional condition, allowing them to take the appropriate steps to reduce stress symptoms and encourage the individual to use better stress coping skills.

This section will look at how IoT-based and wearable gadgets might aid individuals with ASD by detecting their actions using various sensors. Then we'll look at the applications and websites that can be used to monitor their behaviour.

Anxiety problems are common in children and adolescents with ASD, with an estimated incidence rate of 40% [77]. Various physiological indicators and markers are considered for physiological and emotional evaluations. Heart Rate Variability (HRV) is a helpful metric that computes the time intervals between two successive R peaks in an ECG signal obtained by an ECG sensor. Jansen et al. found some evidence of heart rate arousal variability in response to public speaking stresses [78]. The total number of breaths, or respiratory cycles, that occur each minute is known as the respiratory rate (RR). The respiration rate might alter owing to disease, stress, and other factors. The respiratory centre, which is located inside the Medulla Oblongata of the brain, regulates breathing rate. The rate of respiration has been proved to be an effective stress indicator.[79]. The conductivity of the skin is measured by the Galvanic Skin Response (GSR). The GSR may be measured by inserting two electrodes on the skin's surface, one of which injects a small amplitude AC into the skin, and the other uses Ohm's Law to calculate the skin's impedance given a certain voltage. GSR has been suggested as a potential stress indicator.[80]

Wearable gadgets for physiological and, to a lesser extent, emotional monitoring are widely available on the market. Cabibihan et al. [81] conducted a review of the academic literature on several sensing technologies that might be used for ASD

Table 1.1 Review of recent literature

Author	Methodology	ML Model	Data Type	Dataset Size	Evaluat -ion metric	Limitation	Year
Carette [53]	An automated technique using on LSTM neural nets that focuses on the saccade portion of eye during reading	LSTM	Eye Trackng	ASD 17,Non 15	Accuracy 83%	Exclusion of Comparison with other NN	2017
Carette [55]	Using color gradients, cohesively represent eye motions into an image-based manner while preserving the dynamic features of eye movement	RF,SVM, LR, NB, ANN	Eye Trackng	ASD 29,Non 30	AUC 90%	NA	2019
Elbattah [54]	a eye tracking scanpath method for ASD classification using K-mean clustering algorithm,and find maximum accuracy with the k value set at four,	Grayscale ,PCA ,t-SNE,Autoencoder Features, K-Means Clustering	Eye Trackng	ASD 29,Non 30	Accuracy 94%	NA	2019
Tao [56]	eye scan path by saliency mapping from CNN generator and discriminator part with encoder, decoder utilising a CNN-LSTM algorithm for classification.	SalGAN, CNN-LSTM	Eye Tracking	ASD 14,Non 14	Accuracy 74.22%	NA	2019
Goel [61]	Optimization algorithm GOA for accelarating ML algorithm	GOA, , LR, NB, KNN, RF-CART-ID3, BACO	AQ-10, Questionnaire	1100	Accuracy of near 100%	Low convegence speed for GOA	2020
Thabtah [63] and Peebles	On several ASD datasets, bagging, rule induction, boosting, and decision trees methods were empirically assessed, with RML outperforming the others.	RIDOR, None, RIPPER, RML, Bagging, CART, PRISM , C4.5	AQ-10, Q-CHAT, Questionnaire	ASD 189 , Non ASD 515	F1 Score more than 90%	Not applied to any toddler dataset	2020
Kupper [64]	ADOS questionnaire based data, minimizing features into only five attributes, classification using SVM	recursive feature selection, kohen cappa, SVM	ADOS, Questionnaire	ASD 385, Non ASD 288	AUC of 82%	Affect of diffrent ML algorthim in selected feature is known	2020
Levy [65]	Collected separate data for child and adult, applied 17 supervised ML algorithms, 10 features from ADOS and SVM, LDA gained most AUC	LR, Lasso, SVM, ADTree, RF, Ridge, Elastic net, Nearest shrunken centroids, LDA, AdaBoost, Relaxed Lasso	ADOS, Questionnaire		AUC of 95%	Impure source and survey of data	2017
Pratama [62]	SVM, RF, ANN applied into AQ-10 datset with 10 fold cross validation	SVM, RF, ANN	AQ-10, Questionnaire	4189 ASD	Sensitivity of 87.89%	absence of feature selection	2019

screening and treatments. Eye trackers, movement trackers, physiological activity monitors, tactile sensors, voice prosody and speech detectors, and sleep quality assessment devices were among the sensing technologies studied. The devices' advantages and usefulness in assisting the treatment of various symptoms of people with ASD, as well as their limits, were evaluated. Tang et al. [82] focused on the integration of a realistic multi-sensory environment (including a facial expression detection module through Kinect V2's HD Face API) to assist in 'reading' the emotions of ASD youngsters. They integrated four sorts of 'meters' in their design to collectively sense users' behavioural patterns, and individual and group emotions as detailed below:

1. Individual physiological (bio-sensory) data: pulse rate, sweat (through a set of Microsoft Band 2 to be worn by the target player).
2. Individual behavioural meters: head, hands, and upper-body movements, gestures and motions (through touch and pressure sensors), and face expression (not included in the present system architecture).
3. Sociometers with integrated sensors, low-cost depth sensors, and RGB-B sensors (two sets of Kinect V2).

Notenboom et al. [83] used physiological signals to evaluate autistic people's emotions, and they created recommendations based on the target group's user requirements. Because the target population is sensitive to stimuli and has difficulty adjusting, certain design criteria are important. As possible designs, a smartwatch, a patch, and an infrared camera were considered. The recommendations were developed as a result of the examination of these designs. The smartwatch came out on top, followed by the patch. An infrared camera isn't the best option. The principles can be utilised to create a wearable that measures autistic children's physiological signals. Northrup et al. [84] created a combination of tailored features in a wearable sensor and mobile app that analyses stress reactivity in children with autism in real-time and sends on spot notifications to a caregiver through a mobile portable device. Below are some example apps which have been made available aiming at this vulnerable group.

1.4.1 Apps and Platforms for Supporting People with Autism

LetMeTalk

The free AAC talker [85] software, which is accessible for both Android and iOS, assists in the creation of intelligible phrases by aligning graphics. This row of photographs may be interpreted as a phrase if the images are linked together in a meaningful way. This program, they believe, is appropriate for autism symptoms, Asperger syndrome, and Autism Spectrum Disorder. AAC stands for aligning images (Augmentative and Alternative Communication). LetMeTalk's picture library includes over 9,000 easy-to-understand photos from ARASAAC (http://arasaac.org).

Additionally, the built-in camera may be used to add existing photographs from the device or to capture new ones. Considering ASD patients have a hard time interacting with neurotypicals or other peers in society, this type of software can be huge assistance in expressing their emotions.

Coughdrop

Symbol based AAC [86] is another AAC app. The history of building Coughdrop is quite interesting. Brian Whitmer, a software engineer and entrepreneur, was looking for an effective communication method for his daughter who had been diagnosed with Rett Syndrome when he came up with Coughdrop. He was disappointed by bad design decisions and outdated technology because of his experience in usability, so he teamed with around 30 Speech-Language Pathologists, Occupational Therapists, and IT specialists to create something better. CoughDrop was the outcome. Brian soon met Scot Wahlquist, whose son had autism and was nonverbal, and the two collaborated to improve CoughDrop for people with any communication requirement. They believed that too many suppliers were attempting to “lock in” clients through proprietary solutions and expensive costs, and they sought to change that. As a result, CoughDrop was made open-source and included open-licensed materials such as free symbols and community-generated boards, as well as all of our word sets, which are all provided under a Creative Commons license. This software is accessible on the App Store, Google Play, and Amazon, and it may also be accessed through web browsers and Windows. This software allows you to communicate with friends and family in a personalised way across numerous devices. With a simple interface and enough support and teaching, one may gradually increase one’s vocabulary. It operates offline with a cloud backup, making switching devices a breeze if something goes wrong. It’s also possible to share boards with others and open-license them for usage by anybody, across classes, and make access management easier. Individuals may plan a successful approach using built-in goal-tracking tools and gain recommendations for how to strengthen communication tactics from community experts. License consumption may be readily tracked and data can be viewed across rooms, buildings, or teams. People may easily travel between classrooms, and access constraints can be simplified.

Applied Behaviour Analysis (ABA)

ABA is a behaviour treatment based on learning and behavioural science. ABA treatment applies what we know about behaviour to real-life settings. The objective is to encourage positive behaviours while reducing detrimental or learning-inhibiting behaviours. Behaviour analysis approaches have been used and researched for decades. They’ve aided a wide range of learners in gaining new abilities, from living a healthier lifestyle to learning a new language. Therapists have used ABA to assist children with autism and other developmental issues. Many strategies for analysing and modifying behaviour are used in Applied Behaviour Analysis. ABA flashcards and games - emotion [87] is a useful program for applied behaviour analysis (ABA) therapists and other professionals who work with students with autism and similar problems. This software is only accessible in the app store and is completely free. Telehealth mode for distance learning is one of the app's features. Designed specifically for intense instruction sessions, create your own flashcards or use the built-in activities. Use photographs from your gallery or look for pictures and gif animations on the internet. Data collecting and automatic grading Multiple student profiles are supported.

Autism Read and Write

Autism Read and Wright is available through a Google Play store app that is primarily developed to enable ASD children in learning the fundamentals of reading and writing. To get started with the reading lessons, click on 'Start - Reading' lessons and 'Start - Writing' lessons to get started with writing. The reading and writing classes are of varying degrees of difficulty. Change the levels by going to Settings - Reading level or Settings - Writing level.

Social Story Creator Educators

Social story creator educators [88] is an iOS device software that can assist children with Autism to better learn how to deal with various social events, as well as allow them to create tales about various occurrences. Autism is linked to reciprocal behaviours, making it difficult for persons with autism to react appropriately to a circumstance. As a result, this sort of tool can assist people who are unaware of how to handle these circumstances.

Rethink Ed

Rethink Ed [89] is a web-based platform that offers autistic children social-emotional learning, mental health awareness, and special education. It guarantees that autistic children have access to the most effective educators who can provide them with a high-quality education. Rethink Ed offers scalable professional development for students with autism, including video models, high-quality lesson plans, and a curriculum. Communication and social skills are emphasised to help individuals with ASD fully engage in their education.

AsDetect

AsDetect [90] is a screening application for people with ASD. This software is a useful tool for detecting ASD early on. It is straightforward to use; simply sign up for the app, then enter the patient's information and complete an evaluation. After completing these procedures, one may check the results and determine whether or not a person has ASD. They created a demographic questionnaire by administering assessments such as The Bayley Scales of Infant Development (BSID)- Third Edition, The Autism Diagnostic Observation Schedule (ADOS), 2nd Edition, The Autism Diagnostic Interview-Revised (ADI-R), and the Modified Checklist for Autism in Infants and Toddlers (M-CHAT).

Mental Imagery Therapy for Autism

The goal of Mental Imagery Therapy for Autism (MITA) [91] aims to provide language therapy for children with autism. It aims to create unique, digital apps based on proven, evidence-based early-intervention therapies designed specifically for very young children with ASD. These apps have the potential to significantly narrow the gap between the quantity of therapy prescribed and the amount of therapy actually received by children with ASD while also improving care quality. MITA's activities use a systematic way of teaching the skill of responding to many cues. The most distinctive characteristic of these exercises is their ability to deliver instruction outside of the verbal realm, which is critical for children with ASD who are either nonverbal or just marginally spoken. While these youngsters may not be able to follow a spoken command (such as "pick up the red crayon beneath the table"), preliminary findings from the pilot research show that they can obey a command provided visually rather than vocally. MITA helps children develop their creativity and linguistic skills. The visual activities are organised methodically to help your youngster learn to notice many characteristics of an item. MITA begins with easy tasks that educate kids to focus on only one aspect of a situation, such as size or colour. The tasks become increasingly challenging with time, requiring your youngster to focus on two things at once, such as colour and size. After the kid has practised paying attention to two features, the program progresses to puzzles that need the child to pay attention to three features, such as colour, size, and form, and finally to problems that require the child to pay attention to an ever-increasing number of qualities.

The Jade

The Jade [92] Autism app aids in the development of cognitive skills by increasing information and improving development. It can act as a mediator in acquiring skills and abilities such as attention and logical reasoning and assisting in problem-solving, strategic thinking, and decision-making. Activities are categorised into degrees of difficulty within each category. Each phase is only unlocked based on the child's performance, following the natural flow of learning and respecting each child's pace and personality.

1.5 Challenges and Future research

The increase of overall ASD cases worldwide has prompted the search for cost-effective ASD evaluation tools. The deployment of rapid and accurate assessment measures based on computationally intelligent techniques, including machine-learning algorithms, have addressed that need. Despite considerable attempts to develop ML-based ASD evaluation tools utilising fMRI, eye tracking, and genetic data, the promising results based on behavioural data necessitate additional investigation. Sustaining correctness, assuring balance data, employing a benchmark dataset, and lowering diagnosis duration are all critical concerns in ASD classification. Despite this, the lack of sufficient dataset size remains a key challenge in CI-inspired detection and support of ASD. Because the symptoms of ASD patients vary and the number of patients who agree to participate in data gathering methods is still low, the amount of data representing each variation of ASD is also very low. Most of the studies are based on data collected from 50 to 300 ASD patients at most, the size of publicly available datasets [50, 51, 58, 52, 59, 60] are significantly smaller than other healthcare-related datasets. Data augmentation is also common in various approaches to increase data instances. Again most of the datasets are based on questionnaires which may not be adequate to capture the subconscious behaviour and social deficits of ASD patients. Due to the limited amount of data, deep learning techniques have limited implementations and a low success rate in detecting ASD accurately. Again to further reduce time and computational complexity, feature reduction and selection algorithms are also employed. ASD detection has been used with several modalities such as questionnaire, EEG, ECG, MRI, eye tracking, eye scan path, simulation and task completion, facial imaging, Neuroimaging, behaviour analysis, body movement, video and audio analysis, genetics, and more. Though numerous attempts have been made for classification from the modalities mentioned above, most of the study consists of classification from only one or two modalities. Again due to the scarcity of data, only shallow ML and DL models have been utilised in most studies. Even though numerous wearable devices can detect and monitor various physiological changes, some apps can detect ASD and track various features. These aren't complete; instead, they serve as a supplement to one another. There is a dire need for a comprehensive platform that can be used to detect, manage, and monitor people with ASD. Mobile and online applications are frequently device-specific, requiring a specific device to function. Robust integration and sharing management systems are also necessary to work with various wearable devices. Although there are some downsides, research in this scope is vast and proper implementation as the product can eliminate most of them.

1.6 Conclusion

Autism spectrum disorder (ASD) is a complex developmental condition that involves persistent challenges in social interaction, speech and nonverbal communication, and restricted/repetitive behaviours. The effects of ASD and the severity of symptoms are different in each person. And in some cases, some people are not diagnosed until they are adolescents or adults. Complex characteristics and symptoms of developmental and cognitive disorders add complications to classifying in clinical decision-making and deterministic computational methods. Computational intelligence algorithms have been utilised broadly to solve developmental disorders, specifically ASD. In this study, the basis of computational intelligence and its effectiveness in detecting and monitoring ASD has been discussed with recent advancements. Screening result is critical in the research of ASD and, therefore, can be improved to properly and early diagnose the specific criteria of ASD. Early and fast detection with more data-centric approaches can be facilitated by generating large benchmark datasets from multiple modalities. The CI methods can still be improved for performance and reliability to be implemented in real-life scenarios. Management and monitoring applications mostly require proprietary wearable devices, which are yet to be openly available for mass use. Again, most of these applications are at the research stage, limiting their usability for actual consumers. Consumer-grade monitoring devices with open standards to aid ASD patients are also needed. Several such mechanisms were discussed in this study with their accomplishments and limitations. Still, much research is needed to diagnose ASD with better accuracy and develop support systems suitable for the mass population without heavy human interactions.

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