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Application of data fusion for automated detection of children with developmental and mental disorders: A systematic review of the last decade

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ABSTRACT

Mental health is a basic need for a sustainable and developing society. The prevalence and financial burden of mental illness have increased globally, and especially in response to community and worldwide pandemic events. Children suffering from such mental disorders find it difficult to cope with educational, occupational, personal, and societal developments, and treatments are not accessible to all. Advancements in technology have resulted in much research examining the use of artificial intelligence to detect or identify characteristics of mental illness. Therefore, this paper presents a systematic review of nine developmental and mental disorders (Autism spectrum disorder, Attention deficit hyperactivity disorder, Schizophrenia, Anxiety, Depression, Dyslexia, Post-traumatic stress disorder, Tourette syndrome, and Obsessive–compulsive disorder) prominent in children and adolescents. Our paper focuses on the automated detection of these developmental and mental disorders using physiological signals. This paper also presents a detailed discussion on signal analysis, feature engineering, and decision-making with their advantages, future directions and challenges on the papers published on mental disorders of children. We have presented the details of the dataset description, validation techniques, features extracted and decision-making models. The challenges and future directions present open research questions on signal or availability, uncertainty, explainability, and hardware implementation resources for signal analysis and machine or deep learning models. Finally, the main findings of this study are presented in the conclusion section.

1. Introduction

Internationally, one in seven (approximately 14%) children and adolescents experience a mental disorder [1]. This amounts to 86 million teenagers between the ages of 15 and 19 and 80 million between the ages of 10 and 14 [2]. Further, childhood mental illness presents one of the leading causes of health burden worldwide [3]. It is estimated that every year, around 45,800 teenagers commit suicide accounting for one individual per 11 min [2]. Suicide is the fifth leading cause of mortality among teenage boys and girls (10–19 years); among adolescents aged 15 to 19, it is the fourth leading cause of death, trailing only traffic accidents, interpersonal violence, and tuberculosis [4]. It is the fourth most common cause of death for boys and the third most common cause of death in girls between the ages of 15 to 19 years. The percentage distribution of young individuals feeling depressed or having little interest in doing things is shown in Fig. 1 [2]. It shows that countries with low- and middle-economic status are affected more. The African and Asian continents have the highest share while the least affected are Ethiopia, Japan, and Spain [2].

Mental illness in childhood can have adverse consequences on family functioning, social functioning and academic outcomes, and can lead to more serious mental illness in adulthood. Up to 50% of adult mental disorders have their onset before the age of 14 years [5], which indicates the importance of early detection and intervention during childhood and adolescence. Unfortunately, very few children with mental disorders receive treatment. Children's mental health (MH) is frequently regarded as distinct from conceptualizations of adult mental health, and more multidimensional due to the developmental

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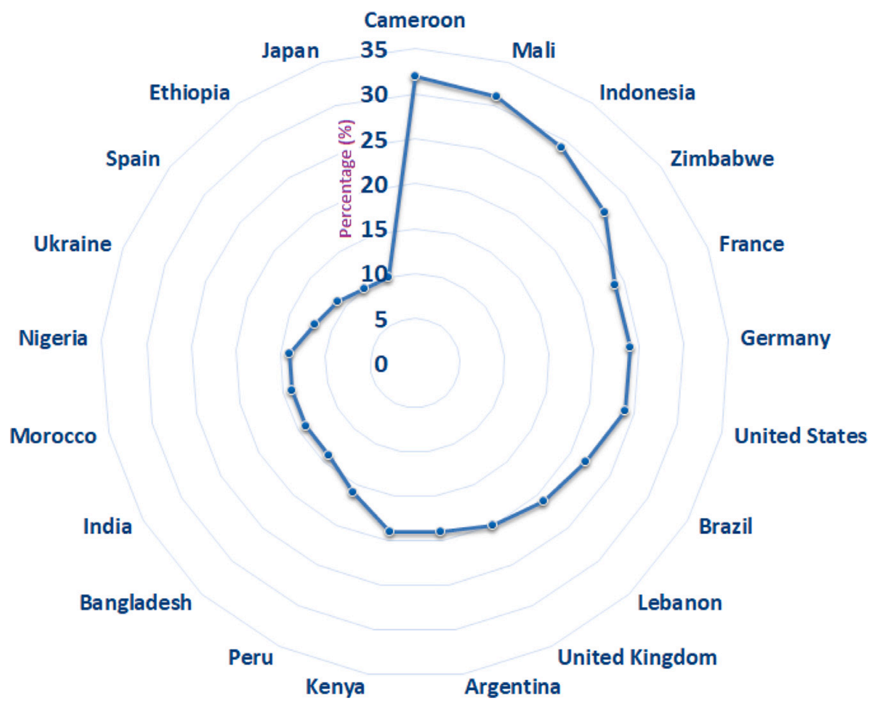

Fig. 1. Country-wise distribution of individuals (aged 15–24) reporting often feeling depressed or having little interest in doing things.

stages children undergo. Therefore, it is essential to examine several MH disorders. The most common and widely exposed developmental and MH disorders are attention deficit hyperactivity disorder (ADHD), anxiety (ANX), depression (DEP), post-traumatic stress disorder (PTSD), dyslexia (DYS), schizophrenia (SZ), obsessive–compulsive disorder (OCD), autism spectrum disorder (ASD), and Tourette syndrome (TS). A brief description of each MH condition is described below:

1.1. Autism spectrum disorder (ASD)

ASD is a neurological and developmental disorder that affects how a person interacts with others, communicates, behaves, and learns. The Diagnostic and Statistical Manual of Mental Disorders (DSM-5) states that people with ASD might show difficulties with social communication and interactions, as well as restricted interests or repetitive behaviors and symptoms that interfere with school, work, or other functioning. Some persons with ASD require a lot of assistance in their daily life, while others may function independently at work. These wide variations in symptoms and intensity associated with ASD are referred to as the "spectrum" [6]. For instance, while some people with ASD are nonverbal, others may have superior conversational skills. Early detection and diagnosis are vital to facilitate early intervention, which can help reduce difficulties, build new strengths, and learn new skills.

1.2. Attention deficit hyperactivity disorder (ADHD)

ADHD is one of the most common childhood neurodevelopmental disorders, which is characterized by impaired attention, motor hyperactivity, and impulsivity [7]. ADHD is usually first diagnosed in childhood, though it can continue through adulthood. Research has demonstrated the role of genetics in the development of ADHD, though environmental risks and other factors, such as brain injury and premature delivery, have also been proposed [8]. There are three types of ADHD, namely: predominantly inattentive presentation (Symptoms: lack of concentration, difficulty in performing tasks, and distractions), predominantly hyperactive-impulsive presentation (Symptoms: talkative, risky activities, impulsive, and impatient), and combined presentation (Symptoms of previous two conditions) [7]. Detection of ADHD can be complex and is required to facilitate the delivery of effective pharmacological and non-pharmacological treatments.

1.3. Schizophrenia (SZ)

SZ is a severe mental illness in which reality is perceived differently. It may include hallucinations, delusions, and severely irrational thinking and behavior, making it difficult to go about daily activities and be incapacitated. Although SZ symptoms might vary from individual to individual, they can be broadly divided into three groups: psychotic, negative, and cognitive (loss of motivation, diminished interest in routine, emotional activities, social disengagement, difficulty expressing feelings, and difficulties carrying out daily tasks) [9]. Risk factor for SZ includes environmental conditions, genetics, and brain structure/functions. SZ patients require continuous attention. Early intervention may help to keep the symptoms under control before major issues arise and may enhance the prognosis in the long run [9].

1.4. Anxiety (ANX)

Anxiety disorders are internalizing disorders and one of the most common MH conditions experienced in childhood and adolescence, affecting approximately 9% of children worldwide [10]. Though anxiety is a normal childhood experience, anxiety disorders develop when children experience persistent or extreme forms of fear and worry that interfere with their functioning. Along with physical symptoms like fatigue, headache, or stomachaches, anxiety symptoms can also include difficulty in sleeping, avoidance of situations that provoke anxiety, excessive worry, reassurance seeking, irritability, and social difficulties [11,12]. Anxiety is highly comorbid with depression. There are several types of anxiety disorders: generalized anxiety, specific phobia, panic disorder, agoraphobia, selective mutism, separation anxiety, and social anxiety. Anxiety is considered to have both hereditary and environmental causes, and treatments incorporate non-pharmacological approaches and pharmacological interventions. Therefore, early detection and intervention is important to the successful management of anxiety [13].

1.5. Depression (DEP)

Although less common in childhood, depression affects approximately 4.4% of young people under 17 years of age [10]. Prolonged sadness and lack of interest are the core symptoms of depression. It affects how one feels, thinks, and behaves and can cause many physical and emotional issues [14]. Children with depression may find it difficult to carry out regular daily tasks, feel hopeless, and not want to do or enjoy fun things and experience problems with sleeping and eating. In teens, symptoms of depression can also include a sense of loss, irritation, and feeling unworthy, and it is also associated with alcohol consumption, self-harm, and suicide. Changes in hormones, changes in brain chemistry, inherited traits, and biological differences are some major causes of depression [14]. Pharmacological and non-pharmacological treatment approaches have been endorsed for child and adolescent depression [13].

1.6. Dyslexia (DYS)

Dyslexia is a learning disability in reading that is characterized by difficulties with accurate or fluent word recognition and poor spelling or decoding abilities and is often a result of deficits in phonological processing [15]. The symptoms include late talking, slow learning of new words, reading, difficulty remembering, spelling, etc. [16]. The causes of dyslexia include genetic and heredity as well as brain anatomy and activity and the condition requires complex assessment to ensure reliable detection.

1.7. Post-traumatic stress disorder (PTSD)

PTSD is a disorder that some children and teenagers can experience after encountering a traumatic event. Traumatic events include experiences that result in serious injury to self or others, such as accidents, natural calamities, physical or sexual trauma, and violence and can be independent or repetitive traumas [17]. Approximately 16% of young people exposed to trauma develop PTSD [18]. According to the DSM-5, PTSD is characterized by four symptom clusters: avoidance, negative changes in cognition and emotions, intrusion, and hyper-arousal [19]. PTSD can negatively affect mental and physical health in addition to diminished social and occupational functioning [17].

1.8. Tourette syndrome (TS)

Tourette syndrome is a tic disorder in which the young person experiences “tics” [20]. Tics are sudden, repetitive twitches, including motions, or noises. Tics sufferers cannot control what their bodies are doing, and for TS, the tics must have commenced before age 18 [21]. There are two types of tics children usually experience during TS, motor or vocal tics [22]. These tics can be simple or more complex. Simple motor tics involve just one muscle group, such as eye blinking or grimacing. The complex motor tics involve more muscle groups and might look like a series of movements. Simple vocal tics include grunting, sniffing, or throat clearing, while complex vocal tics can be involuntary swearing, calling out, or repeating other people’s words [22].

1.9. Obsessive–compulsive disorder (OCD)

Obsessive–compulsive Disorder (OCD) occurs when young people experience recurring, unwanted thoughts, ideas, or obsessions. To manage these thoughts, people feel driven to do something repetitively, actions known as compulsions (also called rituals) [23]. Common compulsions include repetitive behaviors such as, hand washing, mental acts like counting, or checking on things like door locks. Children and adolescents with OCD become trapped in a stressful loop of these thoughts, worries, and routines, and being unable to engage in these behaviors can cause great distress. Only 1%–4% of young people experience OCD [24]. The causes include personality, life events, family history, differences in the brain, and genes [25].

1.10. Motivation for the review

The prevalence of mental disorders in childhood and adolescence and the negative consequences that typically accompany mental disorders highlight the need to establish effective systems for detection and intervention. While diagnostic criteria are available to facilitate diagnosis, this first requires the detection of symptoms or risk and referral to the expert assessment. Detection of MH problems in young people is still hindered by a lack of awareness and MH literacy, the stigma around mental illness, the lack of accessible services, and the lack of universal screening procedures [26,27]. Thus, many children and adolescents with mental disorders are not identified early, and the impact of the disorder may continue into adulthood [27]. There is an opportunity to establish alternative methods of mental illness detection, which may be able to be more easily integrated into routine practice or facilitate self-detection. Advancements in technology provide a unique opportunity to utilize physiological data collected during routine care or the use of apps, to facilitate mental illness detection.

To address this, we aim to provide a systematic review and meta-analysis for MH detection in children and adolescents using different physiological measurements. In our paper, we have included the nine most prominent mental disorders among children and adolescents. The major contributions are listed below:

1. Exploring nine different mental and developmental disorders along with their modalities (neuro-physiological signals).
2. Identify the research gap and provide ways to tackle them.
3. Possible solutions to detect most common mental disorders.

The structure of the paper is shown in Fig. 2.

2. Background of automated detection systems

Over the years, many modalities have been used to detect the MH conditions of children and adolescents. Some of the available modalities which have been used for the detection of MH conditions among children is shown in Fig. 3.

Expert interviews, computer-based assessments/aptitude tests (CPT), read/writing tests, etc., are some manual ways used for MH condition detection. Expert interviews involve clinician-administered questions with young people and parents to determine whether diagnostic criteria are met from clinical symptoms reported. Questionnaires are often employed to gauge distress or symptom levels, family relationships, and child behaviors and impacts on functioning. For some disorders (e.g. learning disorders), children also need to complete neuropsychological testing to identify problems in cognitive, learning, or academic functioning. Children’s performance in CPT is evaluated based on their capacity to recognize, count, and respond to numerous activities presented on a computer screen or other display. Nowadays, the assessment of mental and developmental disorders involve interviews/questionnaires as a standard component. However, implementation of manual detection methods is time-consuming, prone to

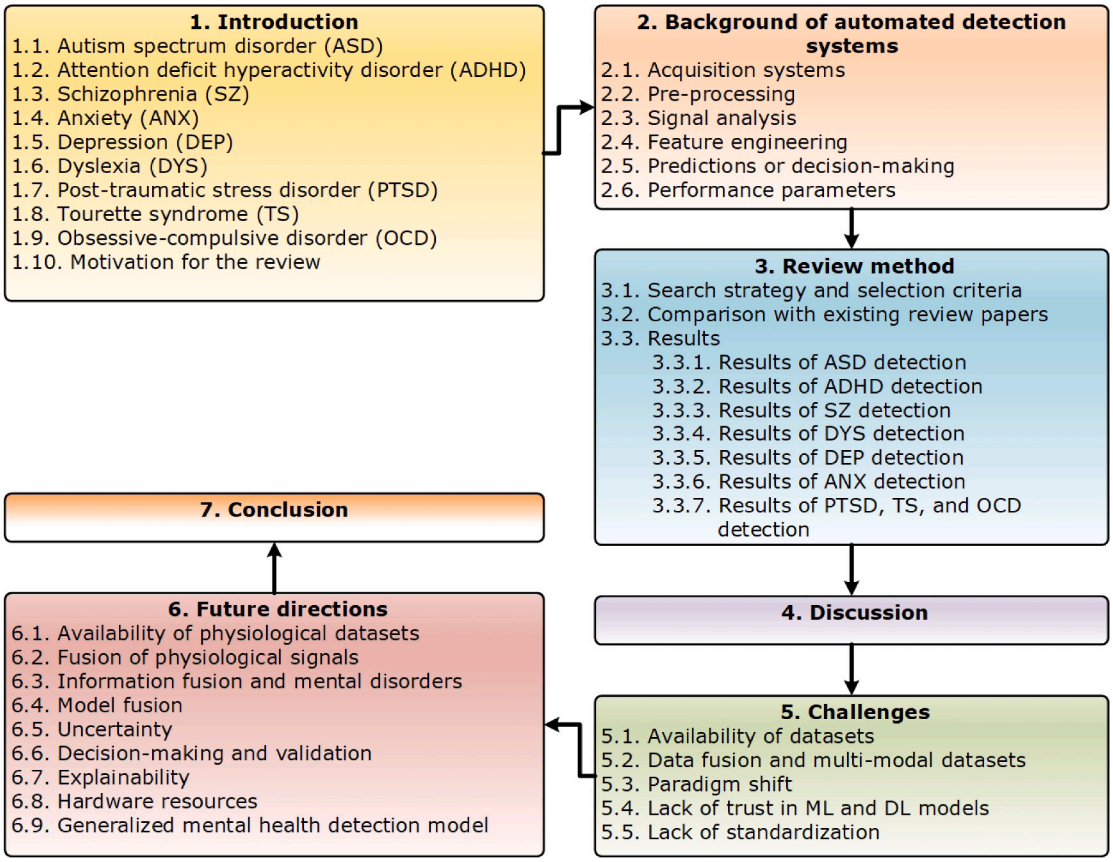

Fig. 2. Block representation of the systematic review.

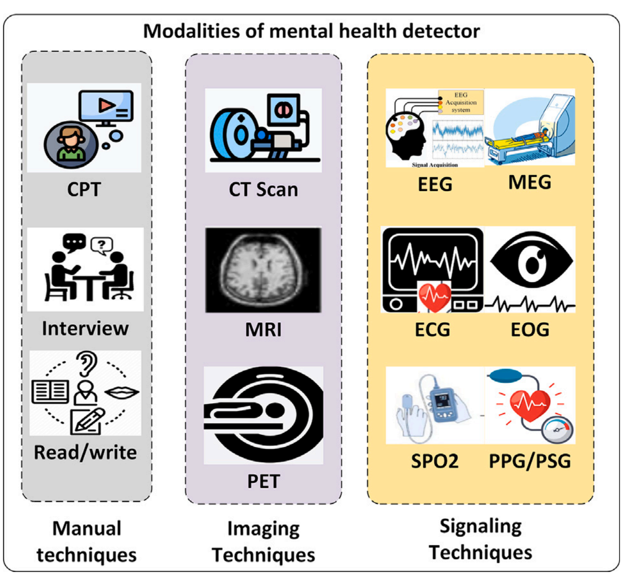

Fig. 3. Available MH detection modalities.

human errors, reliant on the expertise of expert clinicians, and occasionally biased. An alternative option to detect the MH conditions is with neuro-imaging techniques, which involve computed tomography (CT) scan, magnetic resonance imaging (MRI), functional MRI (fMRI), positron emission tomography (PET) scan, single-photon emission computed tomography (SPECT), etc. Such techniques are based on the correlation between cerebral blood flow and neuronal processing [28]. The brain's anatomy is revealed by CT scans using X-rays, including information on blood perfusion (plates a and b); however, the resulting two-dimensional images are of poor quality. By monitoring the blood flow as a result of the person executing a specific task, the fMRI can identify the brain area engaged or actively operating. The radioactivity of substances known as radiotracers that are injected into the bloodstream is measured by a PET scan. The distribution of the chemicals throughout the brain is depicted in 2- or 3-dimensional images created by computer processing of the positron emission data. As blood is a slow and indirect indicator of cerebral activity, the approaches in this category have poor temporal resolution during brain activity measurement [29]. A SPECT scan is a type of nuclear imaging test, which uses a radioactive substance and a special camera to create 3D pictures [30]. The key benefits of SPECT scanning are it is easily accessible, popular, and affordable than PET [30]. But, SPECT takes long scan periods and yields low-resolution images which may be prone to artifacts and attenuation [30]. While methods like the PET scan offer a radioactive answer. These imaging techniques are also expensive, call for additional recordings, and take a lot of processing work. In addition, compared to signaling processes, neuroimaging techniques are more expensive and demand more recording and processing time. The signaling techniques are non-invasive, non-radioactive, low-cost, and portable solutions.

The signaling techniques include modalities like electroencephalogram (EEG) signals, electrocardiogram (ECG) signals, photoplethysmography (PPG) signals, electrooculogram (EOG) signals, electromyogram (EMG) signals, magnetoencephalogram (MEG) signals, polysomnography (PSG), and many more. Among these, EEG and MEG are the most widely used modalities to detect MH conditions. MEG can record brain activity by detecting the magnetic field created by the electrical changes of neurons. A highly sensitive magnetic field meter known as a superconducting quantum interference detector measures the minute magnetic field produced by neural processes [31]. To prevent the impact of outside magnetic noise on the brain-generated magnetic field, MEG requires a particular magnetically shielded environment. To detect the MH conditions of an individual, EEG signals have been widely used [32,33]. EEG recording is the electrical activity-based method used for analyzing brain patterns. EEG acquisition offers excellent temporal resolution, function in a practical environment, and portable and cost-effective solutions. The study of different brain states through electrical activities is made possible by EEG signals. The 10–20 electrode positioning device is used to position EEG electrodes over the individuals' heads. Different behavioral, diagnostic, therapeutic, and neuropsychiatric states of the brain are reflected in the EEG signal and are made up of several fundamental frequencies or rhythms [7,34,35]. The electrical activity of the heart is captured by an ECG. Each cardiac cycle results in the depolarization and repolarization of the cardiac muscle, detected by these electrodes. Numerous cardiac disorders, including cardiac rhythm disruptions, cause changes in the typical ECG pattern. The EOG signals track variations in the electrical potential of the cornea, the eye's positive anterior surface, the retina, and its negative posterior surface. An examination of muscular electrical impulses is called an EMG. Surface EMG is the name of the information-recording technique used for these muscular motion potentials. PPG uses infrared light to gauge the volumetric changes in blood circulation. This measurement provides significant information about the cardiovascular system. Due to its ease of use, wearability for users, and affordability, PPG technology has lately gained appeal as a substitute for traditional heart rate monitors. The common practice is to combine imaging/signal techniques with questionnaires under the supervision of a clinical experts. Clinicians use international standards or protocols as ground truth for different imaging/signal techniques.

Fig. 4 shows the computer-aided design used to detect various MH situations in the meta-analysis. Signal acquisition, pre-processing, signal analysis, feature extraction, and classification are the steps of the automated system.

2.1. Acquisition systems

Acquisition systems are the sources used to measure different activities of the body organs. The electrodes or sensors capturing these activities are placed at the sites specified by international standards [36,37]. The acquisition protocols and the procedure is explained to the participants by the experts before measuring the signals. The choice and number of signals depend on the experts involved in detecting the specific MH disease [38,39]. The signals acquired from the sensors are analyzed individually or collectively [40,41].

2.2. Pre-processing

Pre-processing is an important step employed on the raw data before further analysis. It involves various steps such as noise reduction, normalization, artifact removal, and feature extraction, which collectively enhance the quality, reliability, and interpretability of the data [42,43]. The pre-processed signal help to gain a deeper understanding of data in ensuring accurate and meaningful insights during the subsequent stages of analysis. The pre-processing step in signal analytics involves filtering, removal of artifacts, and other associated noise [44]. This step plays a key role in cleaning the signal to be examined. Pre-processing is making the signal ready for further analysis.

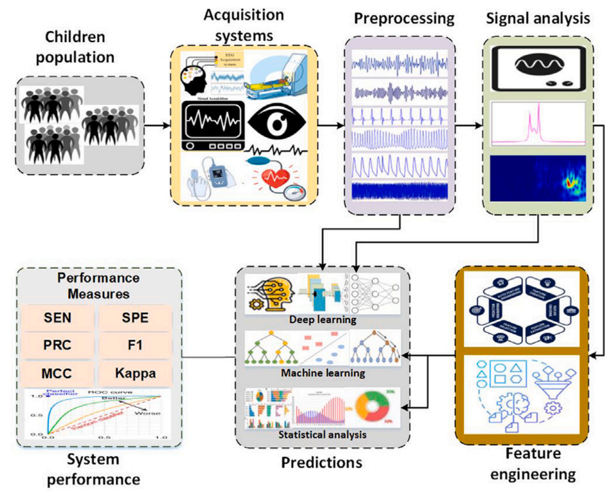

Fig. 4. Steps involved in automated detection.

2.3. Signal analysis

The body instantly alters its physiological and behavioral responses, as seen by the neurophysiological markers [45]. The health conditions of the individual are encoded in these signals. But these signals are non-stationary and nonlinear hence, it is challenging to analyze these signals. Analyzing these physiological signs is necessary to recover the encoded information. These signals are subjected to nonlinear decomposition, nonlinear time–frequency representation, chemical graph-based models, and time-domain analysis [46,47]. Time-domain analysis examines the signal using filtering and fixed-length windowing techniques. A signal is transformed from time to frequency during a frequency-domain analysis. Time–frequency analysis is used to analyze time and frequency features simultaneously. Much attention has been paid to the time–frequency representation (TFR) analysis due to improvements in decision-making brought about by ML and DL methodologies. Nonlinear techniques include signal decomposition that splits the time or frequency domain signal into multi-components.

2.4. Feature engineering

Any automated system's decision-making process heavily relies on features [48]. Features refer to important qualities or traits that are utilized to pinpoint the underlying modifications in the original or transformed signals. A crucial component of automated systems, feature engineering provides essential signal characteristics and aids in signal dimension reduction. Following feature extraction, statistical analysis (SA) is performed to identify and choose the most discriminating characteristics that can be utilized to determine a person's physiological or mental condition.

2.5. Predictions or decision-making

The features extracted and selected using statistical analysis are given to automated decision-making models. The models can be predictors or classifiers used to detect variations in physiological signals. For this statistical analysis, ML and DL modalities are used [45]. The ML and DL models provide automated decision-making in time-, frequency-, time–frequency-domain, and/or nonlinear features [45,49]. Most of the available automated children's mental disorder detection systems have employed supervised ML techniques. Traditional ML techniques have used user-defined feature sets called labeled or structured data to train the algorithms to make predictions [50]. Traditional ML models like support vector machine (SVM), k-nearest neighbor (KNN), decision tree (DT), artificial neural network (ANN), random forest (RF), logistic regression, linear discriminant analysis, etc., are some of the most widely used techniques [47,51]. DL uses ANN to simulate the working of the brain using neurons. Feature representations are automated using multi-level representation: low-mid-high being extracted as inputs for learning at various phases. Learning starts with the nonlinear transformation of input data at each input layer node to generate intermediate output known as features. These features are collectively summed up and applied as input to the next layer. The process is repeated until the last output layer where the decision is made based on some activation function (sigmoid or softmax). Architectures namely convolutional neural network (CNN), long-short term memory (LSTM) networks, deep neural networks (DNN), multilayer perceptron (MLP), recurrent neural network (RNN), generative adversarial networks, gated recurrent units, self-organizing maps, deep reinforcement learning, deep transfer learning, autoencoders, transformers, and deep belief network (DBN) are some of the state-of-the-art DL models which can be used for the automated mental health of children [52].

2.6. Performance parameters

Finally, many evaluation metrics can be computed to determine the system's effectiveness and performance. These evaluation metrics show how well the created automated system performs both individually and collectively. The choice of performance metrics depends greatly on the class population. The confusion matrix, accuracy, sensitivity (recall), specificity, precision, F-1 score, Mathew's correlation coefficient, negative predictive value, false negative rate, false positive rate, Cohen's kappa score, and receiver operating characteristics may be considered to evaluate the performance of the model [7,9,33,53]. In our review method, we used accuracy, sensitivity (recall), and specificity as an indicator of effectiveness. Higher performance indicator values represent the model being effective for the automated detection of developmental and mental disorders.

3. Review method

The recommended reporting elements for systematic reviews and meta-analyses (PRISMA) criteria were followed in conducting the current systemic review [54]. The search technique, selection standards, and data extraction were all included in the review protocol. The following subsection explains the parts:

3.1. Search strategy and selection criteria

We conducted a thorough search to locate the needed studies on physiological signals, artificial intelligence, and children's mental health. We looked into the Web of Science, IEEE Explore, Medline, and Scopus electronic databases. The English-language articles were taken into account. We have limited our search to papers on physiological signals, artificial intelligence, and children's mental health that were published between 16 December 2012 and 15 December 2022. We have searched mental health with ‘‘children mental health using physiological signals’’, ‘‘mental health in adolescents using’’, ‘‘mental health of children using’’, ‘‘schizophrenia in children’’, ‘‘schizophrenia in adolescents’’, ‘‘attention deficit hyperactivity in children’’, ‘‘attention deficit hyperactivity in adolescents’’, ‘‘ADHD in children’’, ‘‘ADHD in adolescents’’, ‘‘autism spectrum disorder in children’’, ‘autism spectrum disorder in adolescents’’, ‘‘anxiety in children using physiological’’, ‘‘anxiety in adolescents’’, ‘‘depression in children’’ ‘‘adolescents with depression, ‘‘dyslexia detection in children using EEG’’, ‘‘post-traumatic stress disorder detection in children’’, ‘‘obsessive–compulsive disorder in children and adolescents’’, ‘‘Tourette syndrome in children and adolescents using physiological signals. The search for physiological signals included ‘‘electroencephalogram’’, ‘‘electrocardiogram’’, ‘‘photoplethysmography’’, ‘‘polysomnography’’, ‘‘magnetoencephalogram’’, ‘‘pulse oximetry signals’’, ‘‘electrooculogram’’, electromyogram’’, ‘‘EEG’’, ‘‘ECG’’, ‘‘EKG’’, ‘‘MEG’’, ‘‘EOG’’, ‘‘PPG’’, ‘‘PSG’’. Finally, the search for artificial intelligence involves ‘‘machine learning’’, ‘‘automated detection’’, ‘‘deep learning’’, artificial intelligence’’, and ‘‘classification’’.

Table 1
Details of inclusion and exclusion criteria adopted for article selection.

Inclusion	(i) mental health of children (up to 18 years)
	(ii) automated ADHD detection in children
	(iii) ASD in children and adolescents using EEG
	(iv) SZ detection in children and adolescents using physiological signals
	(v) DEP in children using physiological signals
	(vi) detection of anxiety using EEG, ECG, EOG, MEG, and other
	(vii) machine learning and deep learning for ADHD, ASD, SZ, depression, anxiety, dyslexia, PTSD, Tourette syndrome, and OCD
	(viii) EEG, ECG, MEG, EMG, EOG, HRV, SPO2, and other modalities for children's mental health
	(ix) PTSD detection in children using EEG
	(x) OCD in children and adolescents using EEG
	(xi) Tourette syndrome detection using EEG
Exclusion	(i) repeated studies of the same applications
	(iii) articles published before 2013
	(iii) non-peer-reviewed articles
	(iv) articles with non-English
	(v) articles including adults

We have designed the inclusion and exclusion criteria to select and exclude the articles from our searched database as shown in Table 1. According to the aforementioned selection criteria, the titles, abstracts, and keywords were individually reviewed in stage one. The authors, after the discussion, have decided on the inclusion/exclusion criterion. Then the full text of the papers was screened in stage two.

3.2. Comparison with existing review papers

We have performed an exhaustive search of available review studies on automated mental disorders. After scanning Web of Science, IEEE Explore, Medline, and Scopus electronic databases we have selected six review articles. The selection criteria used for review articles include keywords like ‘‘mental health EEG review’’, ‘‘mental health and physiological signals review’’, and ‘‘mental health EEG’’. Bardeci et al. explored the review of deep learning techniques applied to EEG signal signals in mental disorders [55]. Armani et al. presented the review of neurological disorders covered using EEG signals and deep learning [56]. Cho et al. covered the review of machine learning algorithms applied for mental illness diagnosis using different modalities from speech, neuro-imaging, physiological signals, and various patient data [57]. Faust et al. presented a review study of deep learning techniques for healthcare applications based on physiological signals [58]. Rim et al. investigated the application of deep learning on physiological data for various medical applications [59]. Su et al. explored a review study on mental health using deep learning techniques for imaging, signaling, voice, and social media data [60]. The graphical overview of the uniqueness of our review study with existing mental health review studies is shown in Fig. 5. The summary of our study with an existing review on mental disorders is shown in Table 2. Based on the gaps in available review studies, we have developed this systematic

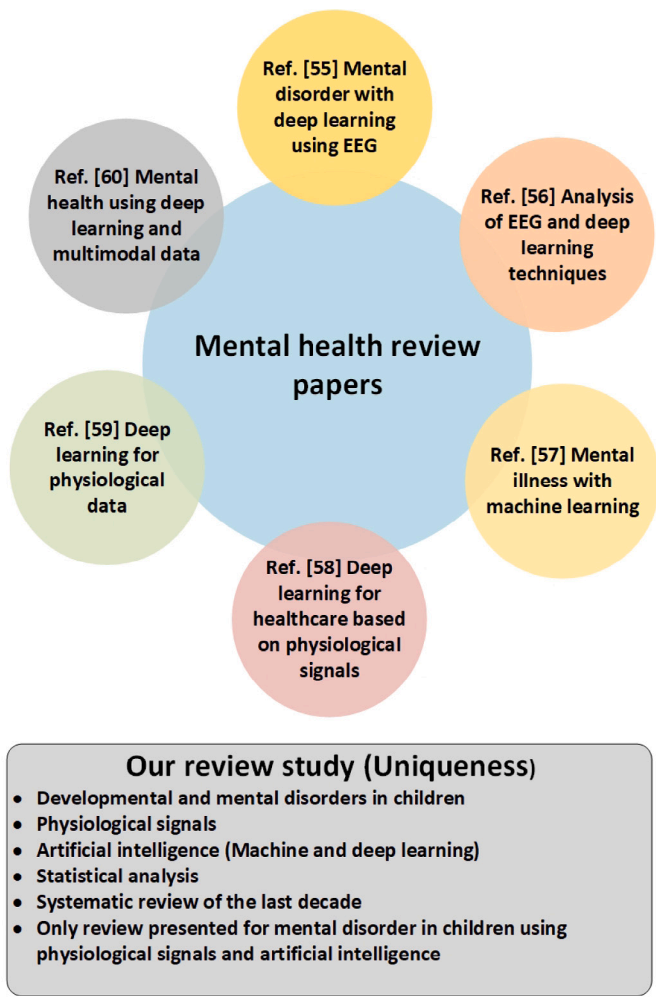

Fig. 5. Comparison of our study with other review papers published in the field of mental disorders.

review and recommendation for future research. This review study explores a comprehensive analysis of physiological signals and artificial intelligence applied for mental and developmental disorder detection in children. To the best of our knowledge, this is the only review study developed for mental and developmental disorders in children using physiological signals and artificial intelligence.

3.3. Results

We have categorized the PRISMA protocol into three steps, i.e., identification, screening, and inclusion, as shown in Fig. 6. Initially, we identified 5007 articles from different databases, including Web of Science, PubMed, and others. After the automated and manual screening, we have selected 783 articles to which retrieval and selection criteria have been applied. After implementing the PRISMA guidelines and steps specified for selection, we have selected 117 articles belonging to nine mental disorder detections. Among the 117 articles, 31 articles belong to ASD detection, 29 for ADHD detection, 17 articles for SZ detection, and 13 articles for dyslexia detection, whereas, 9, 7, 4, 4, and 3 articles were included for depression, anxiety, PTSD, TS, and OCD detection, respectively. The year-wise and publisher-wise distribution of the articles is shown in Fig. 7. The highest 36 articles were selected in the year 2022, while, the least count of 3 articles were included from 2016. We have included the highest 34 articles from Elsevier while 22 and 26 articles from IEEE and Springer.

3.3.1. Results of ASD detection

Many studies have been conducted on the automated detection of ASD using EEG signals. They have used various engineering applications to extract hidden information encoded in the EEG signal. Table A.5 in Appendix A indicates the summary of works done on ASD detection using physiological signals. Three methods have used EEG as a base signal with spectral power, coherence, entropy, and graph connectivity features to detect significant differences between the subjects with and without ASD using statistical analysis (SA) techniques. In our review, we have used four evaluation markers namely ACC, SEN, SPE and sometimes AUC (when ACC, SEN, and SPE are not reported) to indicate the performances. The reason for including these three performance matrices is that it has been widely explored in most of the studies. It is evident from Table A.5, ACC values were reported covering a range of 68% to 100%, for SEN 69% to 100% and 71% to 100% for SPE. The domain and year-specific distribution of articles included in the review is shown in Fig. 8. The pie diagram indicates articles utilizing ML- and DL-based modalities. It is evident from Fig. 8 that EEG is the most widely used physiological signal along with ET, facial, and fused signals. ML-based decision-making has been used more than DL-based methods. Additionally, since 2019, ASD-based studies have been in decline and recently it has started to increase gradually.

3.3.2. Results of ADHD detection

The summary of results obtained for automated ADHD detection in children and adolescents is shown in Table A.6. It may be noted from the table that EEG is the most widely used physiological bio-marker for ADHD detection. Out of 29 articles included for automated ADHD detection, all the articles used EEG while only one used a fusion of fNIRS and EEG for the analysis. The performance report indicates that the highest ACC of 99.95%, SEN of 100%, and SPE of 99.89% has been achieved on one public EEG dataset, while an ACC of 83% has been reported on a second public EEG dataset of 144 subjects [7,61]. The domain and modality distribution used for ADHD detection and the year-wise distribution of articles is shown in Fig. 9. The figure shows that ANN and its variants, such as MLP and extreme learning machine (ELM) classifiers have a clear advantage in ML-based detection, but KNN and SVM classifiers have performed well in ADHD detection. In DL-based detection, CNN outperformed LSTM-based approaches. Furthermore, the year-by-year distribution shows that EEG-based ADHD detection in children gradually increases.

3.3.3. Results of Schizophrenia detection

The summary of physiological signals-based SZ detection in children and adolescents is shown in Table A.7. We have obtained 17 articles on SZ detection from adolescents (up to 18 years) with 16 EEG-based articles and 1 MEG-based article. It is also noteworthy to mention that the highest ACC of 98.3% was obtained for SZ detection using the public EEG dataset with 84 adolescent (up to 14 years) subjects [62]. In this review, only 3 articles have used private datasets, whereas 14 articles have used a public dataset (Same adolescent EEG dataset). The variations in prediction techniques and year-wise distribution of SZ detection articles are presented in Fig. 10. It may be noted from the figure that clinical experts prefer EEG-based modalities. We have found that DL-based detection is more prominent than ML-based detection for SZ in adolescents. Also, CNN-based techniques are more widely used in DL-based predictors whereas, in ML-based detection, SVM and DT models are more frequently used for SZ detection.

3.3.4. Results of dyslexia detection

The discussion on DYS detection in children and adolescents using physiological signals is presented in Table A.8. We have included 13 articles using EEG and EOG signals for the DYS condition. Out of this, 12 articles used EEG signals, while one article used EOG for DYS detection. All articles in the review protocol have used private EEG and EOG datasets. The articles based on functional connectivity with SVM-based

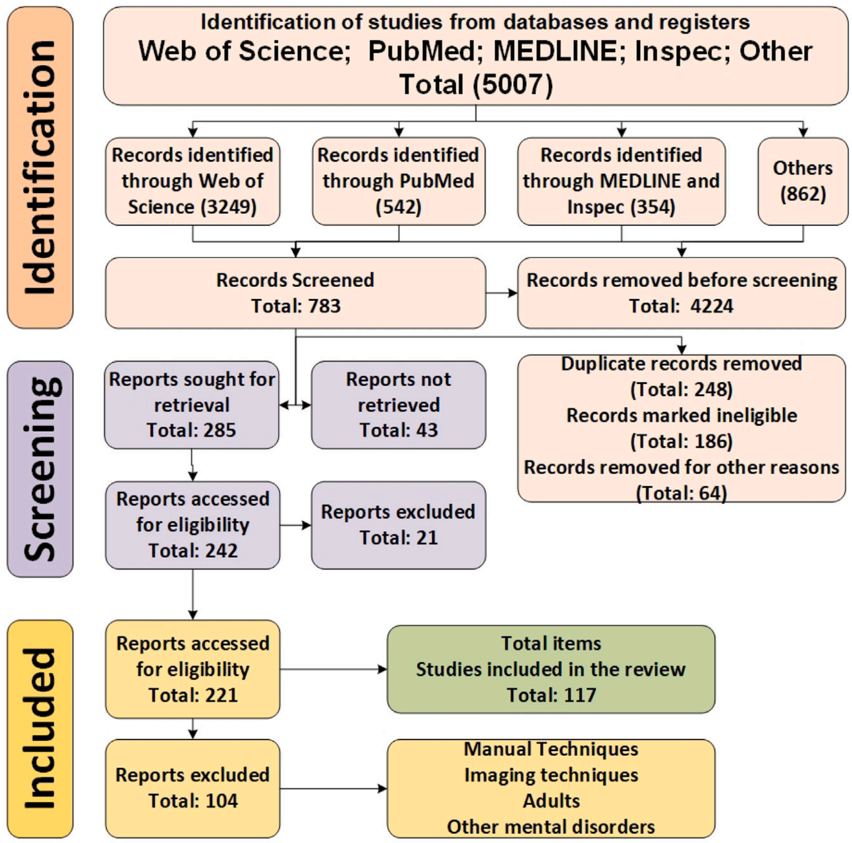

Fig. 6. PRISMA protocol followed in selecting the articles in the review methodology.

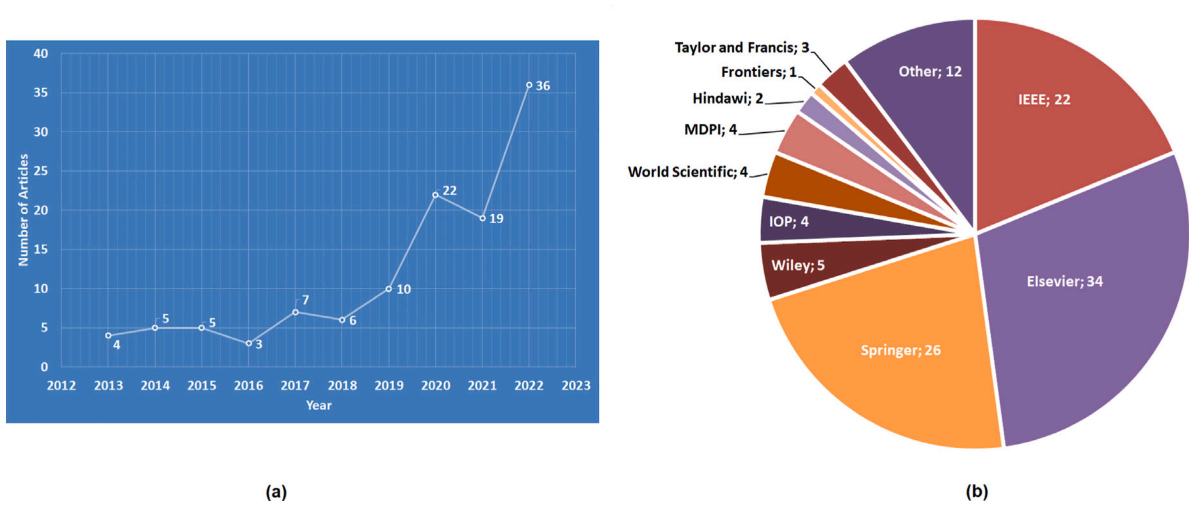

Fig. 7. Summary of the papers included in the review after PRISMA guidelines; (a) Year-wise distribution and (b) Publisher-wise distribution.

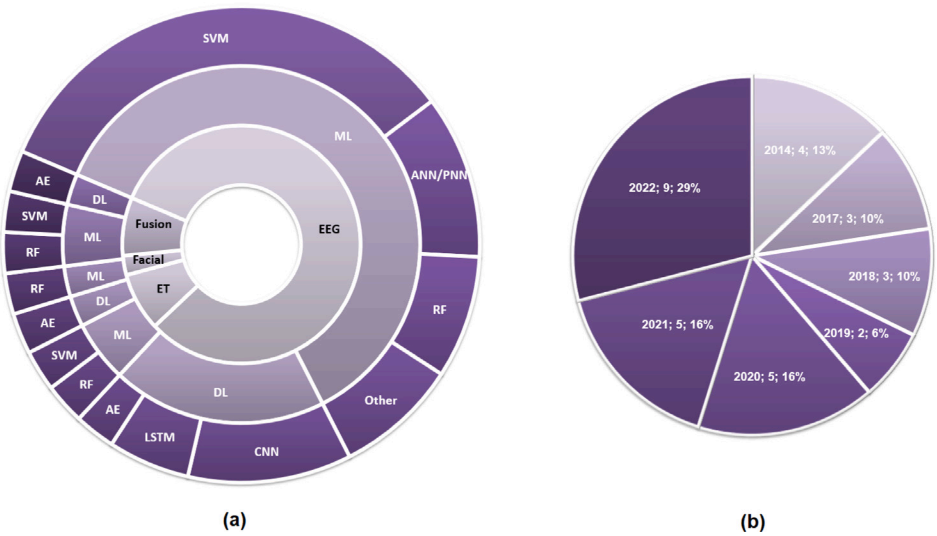

Fig. 8. Summary of ASD detection articles; (a) Predictor distribution and (b) Plot for year-wise distribution (time-based analysis).

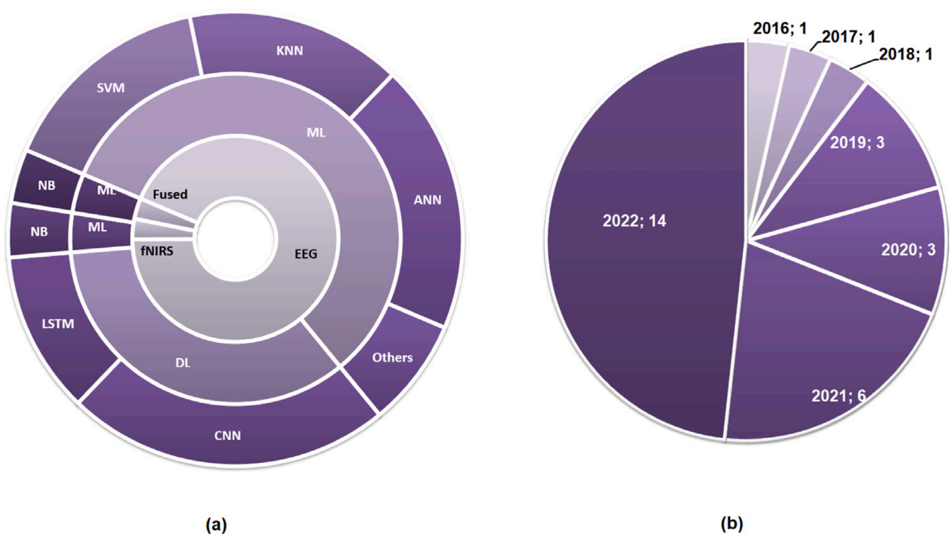

Fig. 9. Summary of ADHD detection articles; (a) Predictor distribution and (b) Plot for year-wise distribution (time-based analysis).

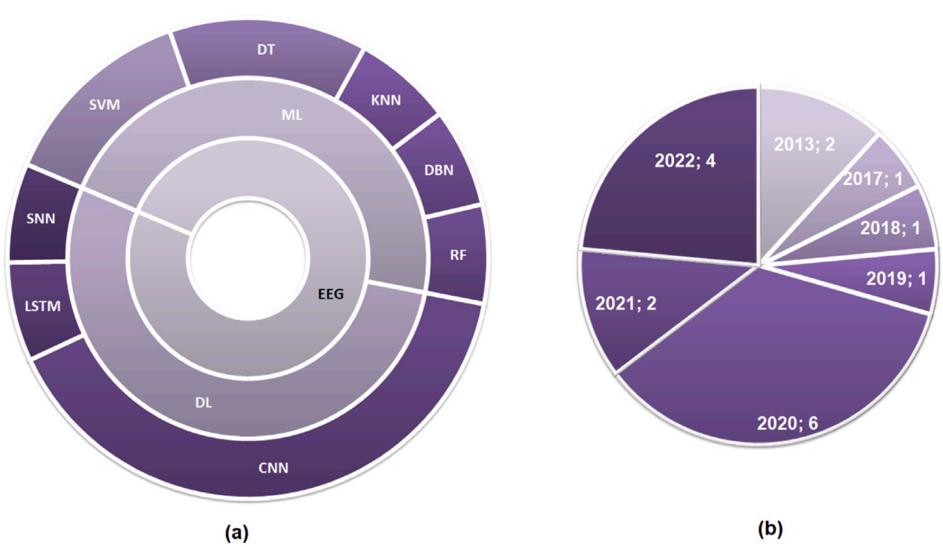

Fig. 10. Summary of SZ detection articles; (a) Predictor distribution and (b) Plot for year-wise distribution (time-based analysis).

Table 2
Summary of our study with existing review studies on mental disorders.

Ref.	Details	Strengths	Weakness
[55]	Psychiatric diseases Application of DL EEG	Systematic review Inclusion of clinical features	Lack of children-related study Use of only EEG-based study Exposure to only DL Shallow discussion on individual disorders Limited future directions
[56]	Neurological disorders Application of DL EEG	Systematic review	Lack of children-related study Use of only EEG-based study Exposure to only DL Shallow discussion on individual disorders Limited future directions
[57]	Mental illness Application of ML Multimodal techniques	Individual discussion on disorders Usage of different datatype	Lack of children-related study Absence of systematic review Exposure to only ML Absence of future directions
[58]	Healthcare Application of DL Physiological signals	Systematic review Usage of different datatype	Lack of children-related study Lack of discussion on disorders Exposure to only DL Limited future directions
[59]	Application of DL for Physiological signals	Usage of different datatype	Lack of children-related study Lack of discussion on disorders Exposure to only DL Limited of future directions Articles between 2018 and 2019 Absence of systematic review
[60]	Mental health Application of DL Multimodal techniques	Systematic review Detailed discussion	Lack of children-related study Lack of discussion on disorders Exposure to only DL
Our study	Mental disorders Application of AI Physiological signals Children's mental health	Systematic review Detailed discussion Future recommendations Signal fusion Discussion on individual disorders Study of the last decade	Absence of clinical features

ML technique have achieved ACC, SEN, and SPE of 95.34%, 96.42%, and 93.33%, respectively [63]. In addition to this, two articles have explored model performance based on AUC. The modality distribution utilizing different prediction techniques and the year-wise distribution of DYS detection articles is shown in Fig. 11. The distribution indicates that ML-based SZ detection has a clear edge over DL-based techniques. The SVM is the most widely used ML-technique for DYS detection. CNN-based models are popular among DL architectures. The year-wise distribution indicates that since 2016 the number of articles published has been increasing except for 2021, with only one article.

3.3.5. Results of depression detection

The DEP detection in children and adolescents using physiological signals is presented in Table A.9. We have selected 9 articles for DEP detection using EEG, EM, and a combination of ECG, EMG, HR, and other physiological signals. The highest ACC, SEN, and SPE of 97.27%, 97.22%, and 97.35%, respectively, were obtained using the DL-based technique with 10 FCV with the public EEG datasets [64]. The other study reported that an ACC and SEN of 99.37% and 99.1%, respectively were obtained using ICA and DL techniques using holdout validation on a private EEG dataset [65]. Among all the articles, one article used a public dataset, seven articles used private datasets, and the detail of one article was unknown [14,38,39,41,64–68]. The modality distribution utilizing different prediction techniques of articles, along with the year-wise distribution of DEP detection, is shown in Fig. 12. The articles have used EEG and EEG with EM and a vocal modality for DEP detection. The ML-based techniques used SVM classifier for DEP detection using EEG, EM, Vocal, and fused features. The CNN-based model with EEG signals was used for DEP detection. The year-wise distribution shows unstable trends, with a maximum of two articles in 2017, 2019, and 2021.

3.3.6. Results of anxiety detection

Table A.10 summarizes ANX detection techniques used in children and adolescents using physiological signals. Seven articles based on different physiological signals have been selected in this review. The separate analysis of EEG and EM signals has resulted in an ACC of 57.47% and 51.13% while fusing these signals has resulted in an ACC, SEN, and SPE of 82.7%, 81.88%, and 83.04%, respectively [69]. Six articles have used private datasets, while one dataset is publicly available. The modalities and year-wise distribution are shown in Fig. 13. The article distribution shows that there is no specific trend; however, since 2021, the number of articles has been increasing.

3.3.7. Results of post-traumatic stress disorder, Tourette syndrome, and obsessive–compulsive disorder detection

The summary of the articles on PTSD detection is shown in Table A.11. We have included four articles in our review, one on each modality based on EEG, MEG, voice, and fMRI. The AUC of 90% has been obtained for the MEG-based model, which uses partial connectivity features, while ACC of 95.2% and 98.25% are obtained for fMRI and speech-based modalities, respectively [70,71]. It is noteworthy that all the datasets used for PTSD detection are private and require special permission. The summary of TS detection modalities is presented in Table A.12. We have identified four articles based on EEG modality. The ACC and SEN of 94.87% and 78.78%, respectively have been achieved using the LSTM-based DL technique, while they obtained an ACC, SEN, and SPE of 65%, 48%, and 82%, respectively, using the CNN-based

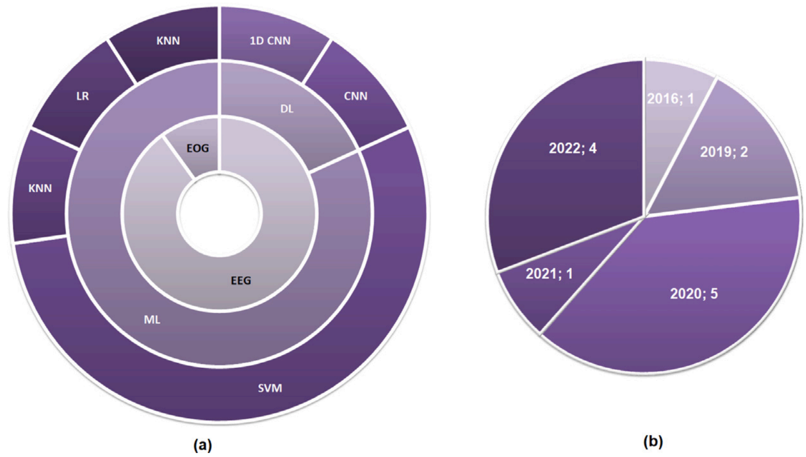

Fig. 11. Summary of Dyslexia detection articles; (a) Predictor distribution and (b) Plot for year-wise distribution (time-based analysis).

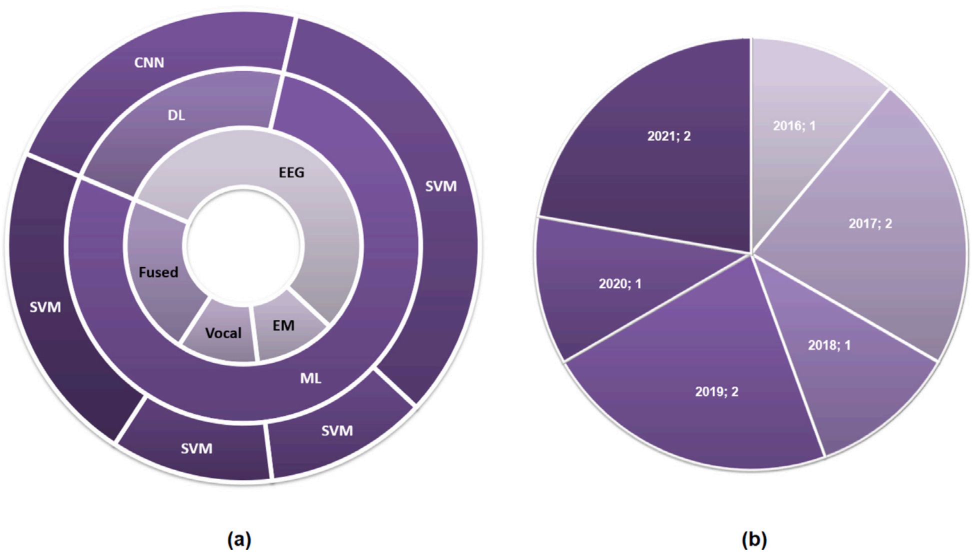

Fig. 12. Summary of depression detection articles; (a) Predictor distribution and (b) Plot for year-wise distribution (time-based analysis).

model [22,72]. All articles in the TS detection review have used private EEG datasets. Finally, Table A.13 indicates the summary of automated OCD detection. Three articles have been included using EEG signals. All the articles used private EEG datasets and reported the highest ACC, SEN, and SPE of 85%, 85.22%, and 84.78%, respectively [73]. The distribution of modality, predictors, and year-wise article analysis is presented in Fig. 14. It is evident from the figure that since 2015 no articles have been reported on OCD, whereas, for TS and PTSD detection, the trend is increasing.

4. Discussion

Mental disorders are highly prevalent and rising in adults and children [4,74]. The distribution of published studies by year included in the review for automated identification of various mental diseases has also revealed similar trends. It can be noted from this work that there is an urgent need for an efficient diagnostic tool that can accurately identify numerous mental diseases. Table 3 contains a thorough summary of the papers that were examined in this review. According to the review study, EEG signals are most frequently employed to identify MH conditions. From our review analysis, we have identified that EEG proved to be the most efficient detection and diagnostic method for detecting MH diseases in children out of all the nine research we considered in our evaluation based on three performance indicators (accuracy, sensitivity, and specificity). The overview of the examined mental diseases also shows that the most popular method for developing an automated system for decision support is ML-based decision-making. DL-based decision-making, however, is also receiving a lot of attention and has been successful in recent years due to the growing number of articles on various MH conditions.

Our findings also show that there are very few public datasets available for analysis which restricts the monitoring or study of multiple mental health conditions at the same time. Among 117 articles belonging to nine classes, only seven public EEG datasets for only five mental disorders are shown in Table 4. We have noticed that even with the existing public datasets, much work has already been done. In addition, the findings reported in these articles have reached their maximum performance. Data fusion can play a crucial role in detecting mental disorders. Our study revealed that fusing data from multi-sensors results in an improvement in system performance. For ASD

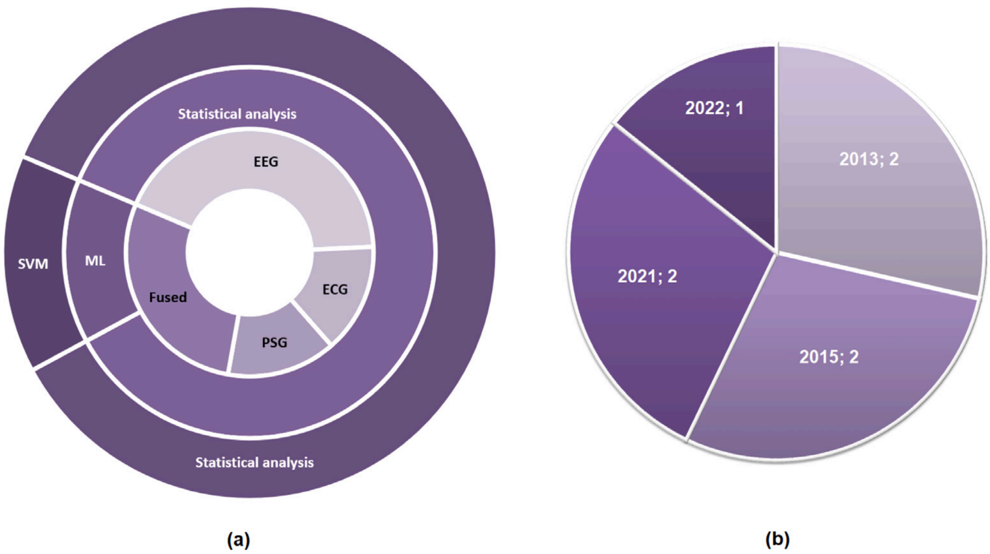

Fig. 13. Summary of anxiety detection articles; (a) Predictor distribution and (b) Plot for year-wise distribution (time-based analysis).

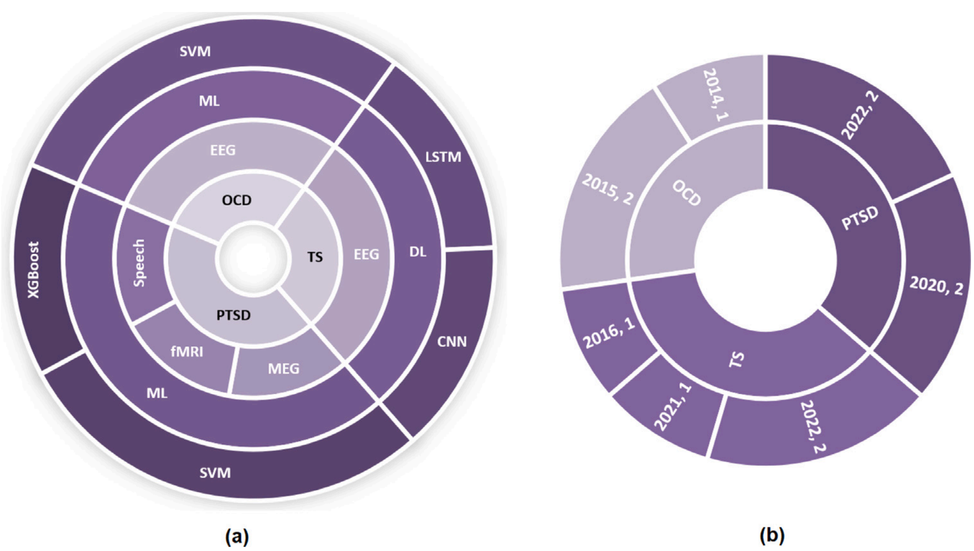

Fig. 14. Summary of other mental disorder detection articles; (a) Predictor distribution and (b) Plot for year-wise distribution (time-based analysis).

detection, researchers have fused EEG, eye tracking (ET), and facial features [80], while, EEG and ET features have been fused in [81,82]. Our study shows that fusing features obtained from different physiological signals increased ACC by 13%–18% for ASD detection compared to a single EEG modality. Only a single fusion technique of EEG and fNIRS has improved accuracy by about 14% and 16% using EEG and fNIRS individually [40]. In the case of DEP detection, EM and vocal have been fused with EEG in [41,66]. Fusing EEG with ET has resulted in an improvement of 2% accuracy, while with vocal data, an enhancement of 3% in ACC is observed. EEG and EM have been fused for ANX detection in [69]. Fusion of sensor data (EEG and eye movement (EM)) has significantly improved ACC by 25% and 31% over separate analyses of EEG and EM signals. There is no uniformity in the validation techniques employed for detecting different mental disorders. The holdout and cross-fold validation techniques share almost equal contributions to system design. On the other hand, LOSO validation has been the least used, with low accuracy scores. The graphical representation of our findings from the review is shown in Fig. 15. From the discussion, it is clear that EEG signals are effective for detecting various mental disorders. The EEG signals can extract hidden changes occurring during mental disorders. The frequency-domain analysis using fast Fourier transform (FFT) and power spectral density (PSD) has been widely used to detect various mental diseases [68,69,80,82–90]. Various nonlinear features and decomposition techniques have been employed to extract representative information from the EEG signals [16,38,44,91–96]. Hence, these features (fractal dimensions and entropy) and nonlinear decomposition, including empirical mode decomposition (EMD), tunable quality factor (TQWT), and discrete wavelet transform (DWT) have been used for mental disorder detection [38,44,73,89,91–94,96–103]. EMD effectively captures the chaotic changes in the physiological signals due to which it has been widely used in physiological signals like EEG, ECG, EMG, etc [38,44,91–93]. On the other hand, TQWT offers an analysis based on a two-channel filter bank with a tunable quality factor, which provides minute details of low- and high-frequency contents of the signals [94,104]. For decision-making, SVM and KNN classifiers are widely used. SVM is widely used in ML techniques as it

Table 3
Summary of mental disorders included in the review with their strengths, limitations, and future directions.

Mental disorder	Strengths	Limitations	Future directions
ASD [75]	• Signal fusion • Well studied • Exposed most of SP and decision-making techniques • Achieved maximum system performance • Explored multiple validation techniques	• Limited public datasets • Varying performance of ML and DL techniques • Already achieved maximum performance on available datasets • Decrease performance with LOSO (including validation and cross-validation) validation • Tested on cleaned and pre-processed data • Limited testing • Models are non-data driven	• Fusion of physiological modality • Fusion of features • Uncertainty • Explainability • Paradigm shift • Public dataset
ADHD [76]	• Increased research exposure • Cross-fold validated models • Detailed system design • Exposed recent and powerful SP and ML tools	• Developed models tested on single dataset • Models are non data-driven • Presented for cleaned and preprocessed signals • Uncertainty in performance • Lack of explainability • Absence of signal fusion • Limited and fully utilized datasets	• Signal and feature fusion • Uncertainty • Paradigm shift • Sustainable SP and ML models
SZ [77,78]	• Diverse models • Exposure to DL-based models	• Only one public dataset • No LOSO validation • Lack of adaptability • validation on a single dataset • Lack of signal fusion • Dataset very small	• Exposure to more public datasets • Fusible modalities • Explainability • Recent DL methods • Uncertainty
Dyslexia	• Models developed for balanced and imbalanced dataset • Well-validated models • Exposed multiple SP models • Robust systems	• Private models • Limited DL techniques • Limited data-driven models • No sensor fusion • Uncertainty • Limited system performance	• Exposure to more public datasets • Fusible modalities • Explainability • Recent DL methods • Uncertainty
Depression [79]	• Simple systems • Fusion of multiple signals • Well validated • Multiple modalities	• Limited LOSO validation • Non-data driven models • Uncertainty • Private dataset • Limited used of SP methods	• Exposure to more public datasets • Exposure to more SP models • Explainability • Recent DL methods • Uncertainty
Anxiety [79]	• Multiple modalities • Simple SP and ML model • Model validated on a public dataset • Signal fusion	• Statistical analysis-based system evaluation • Only one public dataset • Vast scope for signal fusion • Limited exposure to SP and ML • Non-data driven	• Exposure to more public datasets • Limited validation • Lack of explainability and reliability • Exposure to DL modalities
PTSD	• Multiple modalities for detection • Simple system model	• Lot of research gap • Lack of signal fusion • Limited exposure to SP and ML • Non-data driven models • Used private dataset	• Exposure to more public datasets • Limited validation • Lack of explainability and reliability • Exposure to DL modalities
TS	• Simple SP models • Use of DL modality	• Single modality for detection • Lack of signal fusion • No exposure to ML • Non-data driven models • No LOSO validation	• Exposure to more public datasets • Limited validation • Lack of explainability and reliability • Exposure to DL modalities
OCD	• Simple SP models • Versatile ML modality • Well validated signals	• Single modality for detection • Lack of signal fusion • No exposure to DL • Non-data driven models • No exposure LOSO validation • Used private dataset	• Exposure to more public datasets • Limited validation • Lack of explainability and reliability • Exposure to SP and DL modalities

Table 4
Links of the available public datasets for various mental disorders.

Mental disorder	Dataset	Link
ASD	Dataset 1	https://molecularautism.biomedcentral.com/articles/10.1186/2040-2392-4-1#MOESM1
	Dataset 2	https://malhaddad.kau.edu.sa/Pages-BCI-Datasets.aspx
ADHD	Dataset 1	https://ieee-dataport.org/open-access/eeg-data-adhd-control-children
	Dataset 2	https://osf.io/6594x/
SZ	Dataset 1	http://brain.bio.msu.ru/eeg_schizophrenia.htm
Depression	Dataset 1	https://figshare.com/articles/dataset/EEG_Data_New/4244171
Anxiety	Dataset 1	https://www.nature.com/articles/sdata2017181

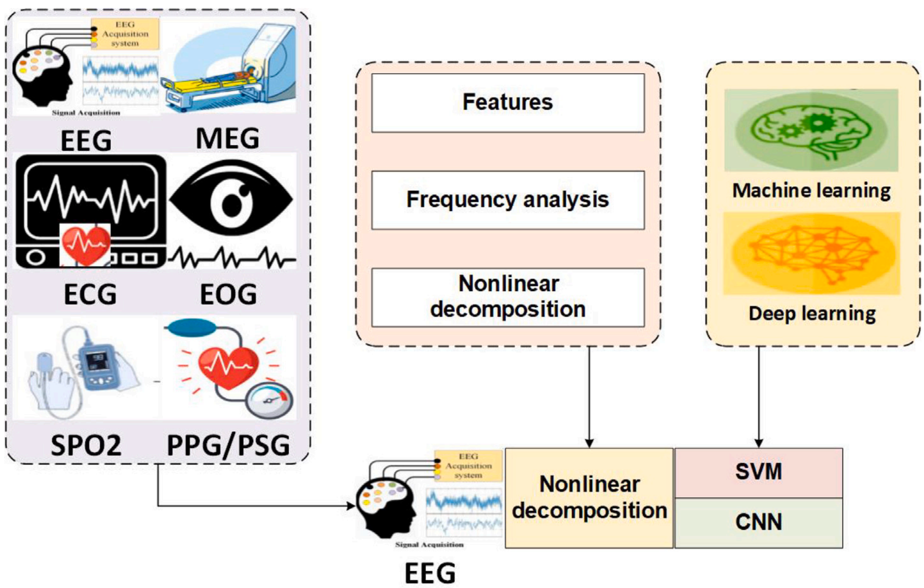

Fig. 15. Graphical representation of findings from our review.

is computationally efficient, better handles the outliers, and is easier to interpret [105]. Also, it outperforms KNN when the number of features are more and training data is few. However, KNN can find very complex patterns, but its output is challenging to interpret. KNN is better than SVM if the training data is larger than a number of features [106]. The combination of time–frequency analysis using short-time Fourier transform (STFT) and continuous wavelet transform (CWT) with CNN have yielded high performance [62,107]. The ability of CNN to extract representative information directly from physiological signals and images makes it an effective and widely used DL model for detecting mental and developmental disorders [34,108–110].

5. Challenges

Based on the discussion, we have identified numerous challenges in the automated detection of mental disorders. The challenges in the existing mental disorder detection are given below.

5.1. Availability of datasets

The public datasets available for mental disorder detection are very limited. Only two public EEG datasets for ASD and ADHD are available, whereas, for SZ and depression, only one EEG dataset is available. For ASD and ADHD, the highest accuracy of 99.15% and 99.95% has been achieved. An ACC of 99%, 98%, and 82% has been reported for SZ, DEP, and ANX classes, respectively. Also, the datasets used by the researchers in their analysis are smaller with fewer subjects. Data imbalance refers to a situation in which the distribution of classes in a dataset is not equal, meaning that one or more classes have significantly fewer samples than others [111]. This can be a problem in machine learning because models trained on imbalanced data can be biased towards the majority class, leading to poor performance in the minority class [111]. The mental and learning disorders in children are usually comorbid. Patients suffering from schizophrenia are comorbid to depressive or major depressive disorder [112,113]. Similarly, children with ADHD are comorbid with depression, disruptive behavioral disorders, and autism spectrum disorder [114]. The same comorbid conditions apply to patients with autism spectrum disorder, where episodes of depression can prevail [115]. However, our review analysis found that very little has been conducted on children targeting the analysis of comorbid conditions [44,53]. This opens new challenges to exploring an analysis of comorbid conditions using physiological signals. Getting normal children's data is difficult and expensive as children coming to the mental hospital are having some problems. Also, usually, children may have comorbid conditions. So it is likely that the few classes during the study may be skewed which may affect the developed model performance.

5.2. Data fusion and multi-modal datasets

Few articles included in this review have explored multiple modalities like EEG with ECG or other modalities. For example, the two articles for DEP and ANX detection have used EEG and ECG in their study [38,67,83,116]. However, the limitation of these articles is that ECG modality is not used for the detection or analysis was done based on the statistical tools without any ML or DL-based decision making. This limits the application of signal fusion to multi-modal analysis. Most learning and mental disorders in children have been detected using cleaned EEG signals. But, acquiring such EEG signals from children is troublesome and interrupted by different noises. Thus, analysis of noisy EEG signals results in uncertainty and degradation of model performance [117,118]. Also, high noise in the EEG signals can result in the loss of crucial information in some instances. Therefore, capturing the physiological changes during such missed events open the scope for detailed analysis of fused data. Acquisition of multi-modal signals including ECG, PPG, EMG, and PSG with EEG and their analysis can help to study variations in physiology during different mental and learning disorders. In addition, analysis of multi-modal signals can help to retrieve the changes in physiology even if some signals get distorted with noise. In addition, the fusion of signals improves system performance as revealed by our review analysis.

5.3. Paradigm shift

EEG signals are highly nonlinear and non-stationary. Therefore, the acquisition of EEG signals requires a noise-free environment which is challenging to achieve. Also, the acquisition of EEG signals from children can be difficult due to low amplitude, frequent movement, motion artifacts, and eye movement which are generally not collected as routine data. In addition, EEG signals involve the analysis of multi-channels and brain regions for effective decision-making. Therefore, a study of children's EEG signals can be more noise-prone. This demands the possibility of exposure to other physiological signals. The brain–heart communication indicates that neuro-developmental disorders can be detected using ECG signals or their combination. A similar study has been reported to detect ADHD and conduct disorder in adults using ECG signals [53]. In another work, authors explored the application of ECG for the detection of psychiatric disorders including, SZ, BD, and DEP [119]. Extraction of heart rate variability and its analysis can also contribute to breakthrough findings in detecting mental disorders. However, ECG signals also require acquisition from multi-channels and suffers acquisition challenges. This demands a simpler technique that involves easier acquisition using wearable devices. This opens new gates for researchers to focus on brain–heart communication or interactions to study mental health disorders in children. To this extent, PPG signals can also measure heart rate variability [120]. Also, the acquisition of PPG is easy due to its capability of easy acquisition techniques from wearable sensors and watches.

5.4. Lack of trust in ML and DL models

An output given by such an automated decision support tool is hard to accept, especially when results are on the other side. Therefore, the stakeholders, experts, and clinicians fail to trust the existing models for their decision. It is due to this reason that even after so many successful technological advancements in signal analysis, feature engineering, and decision-making, these models fail to win the trust of experts. In addition, there are few events where real-time decision support systems are deployed in hospitals and research institutes. This is because the existing mental disorder detection techniques are unable to explain the predictions made by the decision support systems. Therefore, explaining the decisions given by the automated model must be presented to the neuro-experts and caretakers to build trust in our decision support system models.

5.5. Lack of standardization

Finally, in addition to the restricted dataset accessibility, the system verification is carried out experimentally using signal processing or automated decision-making by ML or DL-based techniques with random validation methodologies. Making a ML or DL model efficient for detecting such brain disorders is important as it can significantly impact the child's future. Training a ML or DL model is extremely simple however making it reliable and effective is difficult as it is prone to bias and over-fitting problems. Therefore, these issues must be addressed effectively to develop effective, trustable, secure, and efficient automated systems.

6. Future directions

The future directions for the automated detection of mental disorders in children are given below.

6.1. Availability of physiological datasets

With the alarming rise in the mental disorder conditions in children and its rising financial burden, it is necessary to develop an accurate automated mental disorder detection. To accomplish this goal, it is required to make data publicly available. The accessibility and permission requirements must be made easy and quick so that the researchers or experts do not have to wait for a long time. The data acquisition protocols and procedures should be made public so that other research groups can mimic the same protocol and obtain more data for research.

6.2. Fusion of physiological signals

It has been proven to be an effective technique for mental disorder detection, especially for DEP and ANX detection. The central nervous system of human-being is designed such that the changes in one organ also show an effect on another. Therefore, brain–heart interaction, brain–eyes interaction, and brain–heart–eyes–muscle communication may prove crucial and helpful in studying changes in different organs. EEG signals are prone to noise, hence making the analysis difficult. Also, it is difficult to capture these signals from children due to their instability in sitting, frequent movements, touching of sensors or electrodes, distraction, eye movements, and other physical factors. Processing such noisy signals may not yield accurate performances. Also, the existing automated systems are developed using pre-processed EEG signals. Therefore, a detailed analysis is required while using other physiological signals like PPG/ECG/HRV/SPO2. It has already been proven that changes in the brain cause changes in the electrical activities of the heart (ECG) [53,119]. Therefore, a paradigm shift or fusion may play a key role in detecting mental disorders accurately. So, we can use ECG signals in addition to EEG signals to obtain details of mental disorders in addition to cardiac conditions. Also, it is relatively easy to obtain clean ECG signals after the preprocessing as compared to EEG signals. The other advantage of PPG is that they do not require special arrangements and multiple electrodes for signal acquisition. The sensors are attached to wristwatches, fingers, or other wearables that are readily available, affordable, and more useful than EEG. The heart rate variability (HRV) signals can be obtained from PPG signals to detect other mental disorders and also other cardiac ailments [120,121]. Also, taking consent from the caretakers or subjects becomes relatively easy as it does not involve any risk or special arrangements. Therefore, this will result in the availability of more public datasets compared to existing modalities. This may pave the way for more researchers to explore hidden characteristics of different physiological signals and sensors. The fusion of physiological signals like ECG, EMG, PPG, EEG, SPO2, etc can be used to detect accurate mental disorders as shown in Fig. 15. Also, a fusion of linear, frequency, and nonlinear features can aid better performance [122].

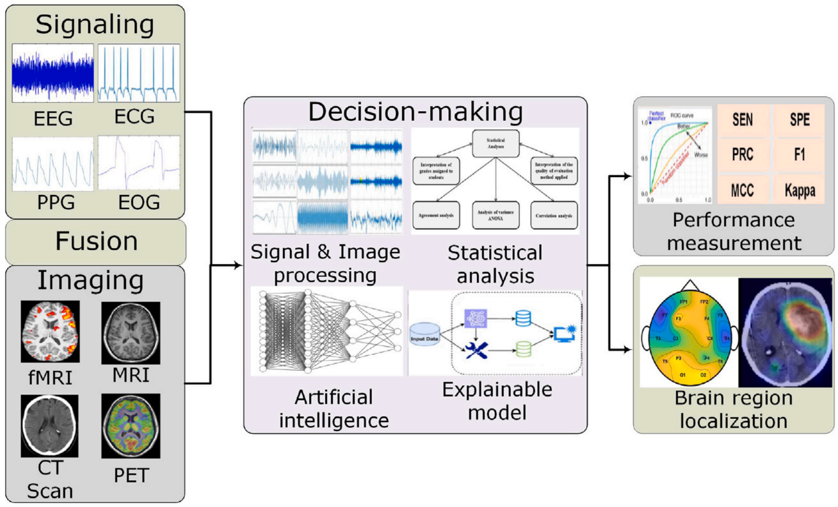

Fig. 16. Fusion-based analysis and localization model for children's mental disorder detection.

6.3. Information fusion and mental disorders

Health-related issues warrant serious concern in childhood. In addition, mental disorders are commonly comorbid with other mental or physical health disorders [4]. Our discussion indicates that information fusion is useful for accurately identifying mental illnesses. Information fusion involves integrating data from multiple modalities, such as imaging, physiological signals, and questionnaires, to gain a more holistic and accurate assessment of individuals with mental disorders. By fusing information from various sources, we can capture a broader range of factors that contribute to these disorders, including biological, psychological, and behavioral aspects. Modality fusion may be useful to boost the acceptance of mental disorders detected by physiological systems rather than the more traditional approach of clinical assessments. The presence of noise and difficulties in acquiring EEG signals from children offer various challenges for clinicians to trust the outcome. Fusing physiological signals obtained from different body parts can help clinicians and experts to make effective decisions in detecting mental disorders. In addition, fusion of physiological signals also helps to improve the system's performance due to its representative characteristics. Also, if the information from one modality is interrupted due to noise and other factors, fusion can map physiological changes from other signals. Currently, while designing a computer-aided decision-making model, researchers rely on single modalities i.e., either signaling or imaging techniques. Signaling techniques can provide important information during the early development of mental and learning disorders, however, care-taker and clinicians offer their assistance [123]. The fusion of signaling and imaging techniques may help clinicians to evident their findings for mental disorder detection due to dual measure and verification [124]. Also, by fusing signaling and imaging techniques, it not only offers scope to improve the system performance, but may also help to localize the brain region responsible to detect the changes during certain disorders. The generalized overview of the proposed fusion-based analysis and localization model for children's mental disorder detection is shown in Fig. 16.

6.4. Model fusion

The variation in data size affects the system's performance. Traditional ML or medium neural networks models perform better on smaller and cleaned datasets [125]. However, with the increase in data size, the performance of traditional ML models gets saturated [125]. Similarly, DL models tend to perform better on big and complex data, due to their ability to extract representative features [125]. Also, DL models require a large amount of time to train and make predictions. However, in real situations, the data size is dynamic and therefore, a single ML or DL model may not give desired performance. To tackle such scenarios, there is a need to develop a robust and fusible decision-making model for effective analysis. Fig. 17 provides an overview of the proposed hybrid and fused decision-making model for mental disorder detection. Also, fusion of DL and ML models can be extremely useful for the early detection of mental disorders. The lightweight transfer learning models can be used to extract the features from the physiological signals. The features extracted from the various lightweight models from the fully connected layers can be fused, ranked and fed to various ML classifiers to choose the best-performing ML model [122]. This can help to obtain high performance with low computational complexity.

6.5. Uncertainty

It is very important to ensure the reliability of AI model, while implementing in the real-time scenarios. Majority of the models presented in the review have been developed and implemented on conditioned and pre-processed signal. However, in the real scenarios, there can be a presence of noise that may change performance of the system. The change can negatively affect system's performance due to introduction of uncertainty. The sources of uncertainty occur due to mismatch in the training and testing data, class overlap, and the introduction of noise in the data [117,118,126]. The data uncertainty is due to irregularities in data but not due to irregularities in decision-making models [117]. Knowledge uncertainty, also called epistemic uncertainty, arises due to inadequate knowledge [117]. The existing models suffer from a lack of robustness and uncertainty. An appropriate selection of tuning parameter, features, and decision-making models are the results of knowledge uncertainty, whereas imbalance in data and introducing noise in data falls under data uncertainty. Such uncertainties in the model may make the model unreliable. Uncertainty quantification (UQ) is the science of quantifying, characterizing, tracing, and managing uncertainty in the data and deep learning models. Several uncertainties such as selection and collection of data, completeness of the training model, knowledge of decision-making models with their performance bounds, limitations, and uncertainties corresponding to the performance of the model based on operational data are required to be quantified and studied [117,118]. To study UQ, a few well-known

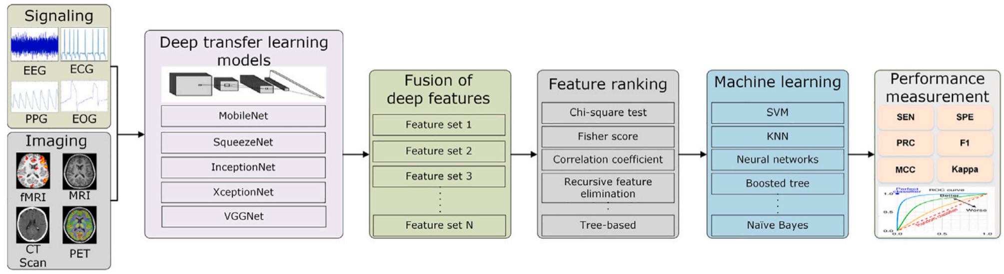

Fig. 17. Overview of hybrid and fused ML/DL model for mental disorder detection.

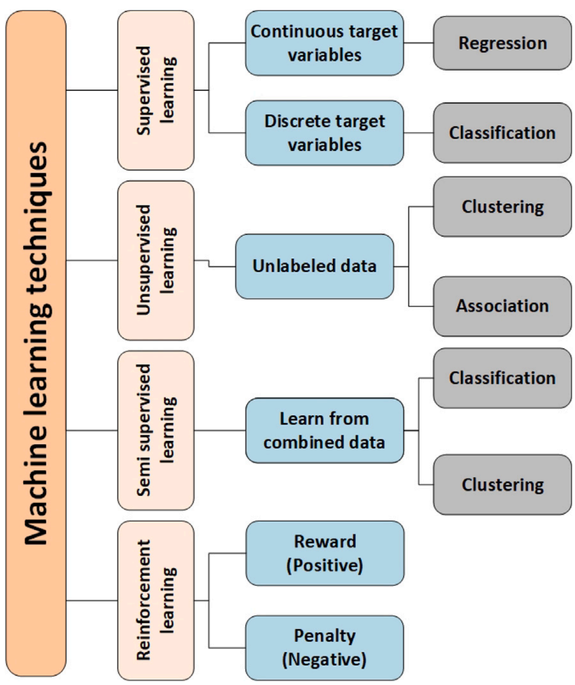

Fig. 18. Taxonomy of machine learning techniques.

models like Bayesian inference, fuzzy systems, Monte Carlo simulation, rough classification, Dempster–Shafer theory, and imprecise probability can be explored to increase trust in the developed model [127]. To address this issues of uncertainty, tuning of parameters and mitigating of noise within the data is required.

6.6. Decision-making and validation

The automated decision support system can play a key role in the decision-making of mental disorders. It can be noted from the discussion that 25% of the articles have used SA, 18% DL technique, 49% explored ML techniques, and 8% the combination of ML and DL-based decision-making. In the ML-based techniques, SVM, ANN, and KNN are the most widely used techniques, while CNN-based models are the most popular in DL-based decision-making. It is noteworthy to mention that all the articles have focused on a discrete binary or multi-class classification for mental disorders detection. In addition, looking at the growing trends in these mental disorders, it is mandatory to explore predictions of these disorders. ML and DL are widely used modalities for decision-making in healthcare analytics. However, experts must have a clear idea about their problems. Therefore, we have categorized the scope and choice of the decision-making modalities based on two constraints: (i) data requirement, and (ii) hardware requirement.

- *Data requirements*: The performance of the decision-making model depends on the quantity and quality of data availability. But, the performance of the traditional ML models reaches a stagnant point after which the model stops learning and results do not improve further. In such scenarios, DL architectures can be used as they are likely to perform better with an increase in the data [128].
- *Hardware requirements*: The DL models are computationally intensive, requiring huge data to train. Graphical processing units (GPUs) or tensor processing units (TPUs) can be used to increase training and testing speed. Also, google cloud services can be explored to run the DL in the cloud. [129].

The detailed ML taxonomy for prediction and detection is shown in Fig. 18. To improve the performance of the existing models, one can use the combination of different learning principles of ML to detect labeled and unlabeled data.

Also, with technological advancement and rapid development in data acquisition systems, the amount of data is increasing. This increase in the amount of data limits the performance of ML-based techniques to a saturated level. In such scenarios, DL techniques play a crucial role in enhancing the system performance. The taxonomy of the available DL techniques is presented in Fig. 19. The current review explores the mental health disorders using CNN, LSTM, AE, and its combination. However, with recent advancements, the available DL techniques along with recent methods like attention and vision transformers, can also be used for prediction and detection. Additionally, the available datasets are unbalanced making their analysis difficult due to class imbalance. In such scenarios, just reporting ACC may not be reliable. Data imbalance algorithms must be used to make the data balanced as well as parameters like precision, recall, Cohen's kappa score, and F-1 score must be used to evaluate the performance.

6.7. Explainability

Explaining individual predictions of ML or DL techniques educates layman or stakeholders about the parameters, features, and brain regions responsible for particular disorder [130]. Fig. 20 illustrates the explainable AI model for explanations of the predictions given by the model. For the existing ML-models, local predictions are identified using Locally Interpretable Model Agnostic Explanations (LIME) and SHapley Additive exPlanation (SHAP) values [130]. LIME is observation-specific because it operates locally and will offer justifications for the prediction in relation to each observation. Using sample data similar to the event being explained, LIME tries to fit a local model. The local model may belong to the category of interpretable models, which includes DT, SVM, KNN, etc. SHAP divides prediction variance

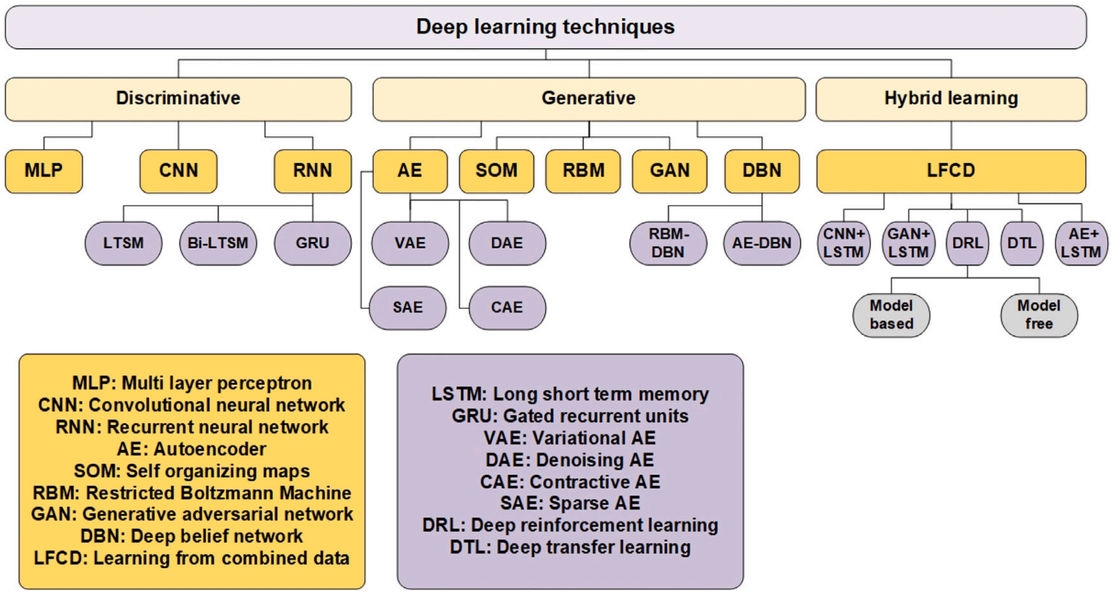

Fig. 19. Taxonomy of deep learning techniques.

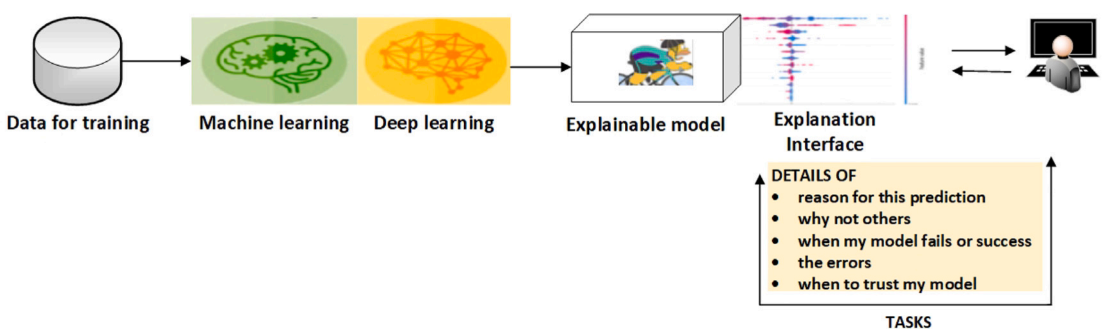

Fig. 20. Integrated explainable AL model for prediction explanations.

across accessible covariates; this allows the significance of each explanatory variable to each point predictor to be analyzed regardless of the underlying model. For the explainability of CNN-based models class activation map (CAM) i.e., heatmaps, has been widely used. Various CAM variants have been developed in this category, including Grad-CAM, Grad-CAM++, SMOOTHGRAD, U-CAM, Eigen-CAM, Score-CAM, etc. [130].

6.8. Hardware resources

The existing models focus on techniques that utilize complex nonlinear functions for analysis and decision-making [131]. These nonlinear functions are developed using floating point operations, resulting in micro-level precision. However, some applications or scenarios make immediate decision-making difficult. To achieve this, edge-implementation techniques are required where processing and decision-making models can be deployed on the model itself rather than processing in the cloud or server. The edge implementation can be done using a graphical processing unit (GPU), application-specific integrated circuit (ASIC), or field programmable gate array (FPGA) [132]. GPUs are efficient in performing these floating-point operations of the developed model but lag in performance compared to ASIC or FPGA [132]. On the other hand, ASIC is one of the best choices due to its performance [132]. But, rapidly developing technology and the initial phase of edge intelligence limits its usage, as the models are not upgraded once deployed or developed. FPGA is preferred over GPU and ASIC devices because of its upgradability and faster performance. But limited resources of FPGA fabric limit the nonlinear operations; therefore, these nonlinear operations are required to convert to piece-wise linear approximation and fixed-point operations to achieve the end goals.

6.9. Generalized mental health detection model

The generalized end-to-end system development composed of many components for accurate mental disorder detection is shown in Fig. 21. It is evident from the Figure that a smart mental disorder detection system includes doctors, patients, data, staff, experts, and a decision-making system. The decision-making can be accomplished using a cloud-centric or edge-centric approach with security, transparency, and upgradation. The local interconnected healthcare system needs to be efficient, fast, upgradeable, and configurable to modification and advancements in technological developments. These local interconnected

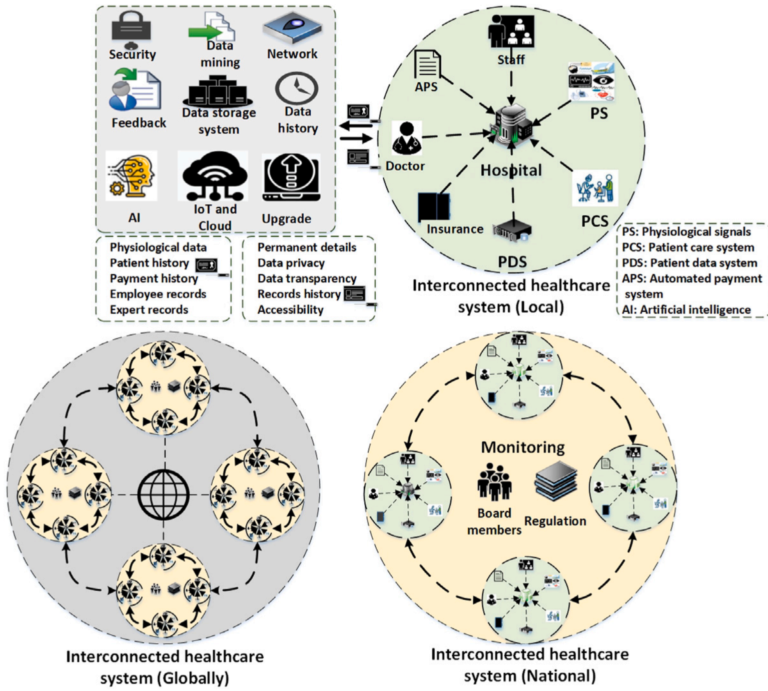

Fig. 21. Overview of global mental disorder detection system with its components.

units are combined to form a regional or national unit with monitoring committees and regulations. These national systems are then connected to the global networks for data upgradation, decision-making, data storage, patient history, and defining the international standards for monitoring periodic mental disorders.

7. Conclusion

Around the world, millions of children and adolescents struggle with various mental illnesses. Despite the medical breakthroughs, there is a steady increase in the suicide and death rates in children. Numerous techniques have been employed to identify and classify mental problems in children and adolescents. Physiological signals are widely used to detect various mental and developmental disorders due to their safe and non-invasive acquisition methods. The EEG signals have been widely used to identify various mental diseases. However, due to its low amplitude, complex collection settings, and significant noise, analysis is challenging and decisions are difficult to accept. Due to the interactions between the brain and other organs, the central nervous system's connection with other vital organs like the heart, muscles, and eyes may reveal details about these organs. Findings about the behavior of organs with numerous mental diseases can be made by switching or fusing the paradigm from EEG to ECG/SPO2, PPG, or their mixtures. Additionally, compared to EEGs, the acquisition of ECG, PPG, and SPO2 signals is simple, requires fewer electrodes, is economical, and has higher amplitude. The SVM-based ML models are most widely used in mental health disorders. Deep learning models are also gaining popularity due to their ability to extract subtle useful information from the signal. However, DL models are not explored to its highest capability due to the limited access to mental disorder datasets. Our findings indicate that the availability of data, lack of standardized protocols, and limited fusibility of sensors or features are the challenges in the existing decision support systems. The automated systems are not reliable to the clinicians as the developed model is unable to illustrate its diagnosis to the clinicians. Also, the performance of the model may vary with changes in the clinical settings. Hence, signal fusion, building effective decision-support models, newer, huge, diverse datasets, explainability, uncertainty quantification, and hardware implementation can yield reliable, accurate mental health detection models.

CRediT authorship contribution statement

Smith K. Khare: Conceptualization, Methodology, Writing – original draft, Validation, and Editing. **Sonja March:** Validation, Reviewing and Editing. **Prabal Datta Barua:** Validation, Reviewing, and Editing. **Vikram M. Gadre:** Validation, Reviewing, and Editing. **U. Rajendra Acharya:** Conceptualization, Validation, Reviewing, and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Appendix A. Summary of the MH disorders included in the review

See Tables A.5–A.13.

Appendix B. Abbreviations

See Table B.14.

Table A.5
Summary of the autism spectrum disorder detection in children studies included in the review.

Ref.	SP Method	Prediction	Modality	ACC	SEN	SPE	Subjects	Strategy	Dataset access
[80]	FFT	ML(RF)	ET	73.75			ASD:40 & HC:40	LOSO	Private
			Facial	77.5					
			EEG	83.75					
			Fused	87.5					
[133]	WT & features	ML(THLD)	EEG	93.3	86.67	100	ASD:15 & HC:15	5 FCV	Public
[134]	SVD & Spectral	ML(SVM)	EEG	92.66			ASD:46 & HC:63	10 FCV	Private
[135]	Segmenta-tion	DL(LSTM)	EEG	99.48			ASD:39 & HC:14	holdout	Private
				97.72	85	96		10 FCV	
[136]	Sparse coding	DL(RSN18)	EEG	98.88	100	96.4	ASD:20 & HC:09	holdout	Public
[137]	Nonlinear features	ML(SVM)	EEG	98.7	97.5	100	ASD:40 & HC:37	10 FCV	Private
[95]	HOS bispectrum	ML(PNN)	EEG	98.7	100	97.3	ASD:40 & HC:37	10 FCV	Private
[138]	mMSE	ML(NB)	EEG	79			ASD:19 & HC:30	LOSO	Private
[139]	MSE	ML(RF)	EEG	92.8			ASD:10 & HC:15	LOSO	Private
[140]	WT & rhythms	ML(SVM)	EEG	100	100	100	ASD:99 & HC:89	LOSO	Private
[141]	RQA	ML(SVM)	EEG	92.86	100	85.71	ASD:16 & HC:46	LOSO	Private
				95.46	93.94	96.97		10 FCV	
[142]	CWT and TFR	DL(SQZN)	EEG	82.98			ASD:13 & HC:04	holdout	Public
[143]	STFT	ML(SVM)	EEG	95.25	97.07	90.95	ASD:12 & HC:04	10 FCV	Public
		DL(CNN)		99.15	99.19	99.04		holdout	
[97]	DWT	ML(RF)	EEG	86	95	71	ASD:96 & HC:47	LOSO	Private
[81]	MSE & Power	DL(AE)	EEG	81.11	82.5	80	ASD:40 & HC:50	10 FCV	Private
			ET	86.67	77.5	94			
			Fused	95.56	92.5	98			
[144]	Coherence	ML(SVM)	EEG (A)	75	69		ASD:46 & HC:37	10 FCV	Private
			EEG (B)	79	84		ASD:37 & HC:46		
			EEG (C)	76	80		ASD:46 & HC:52		
			EEG (D)	79	72		ASD:20 & HC:42		
[122]	STFT & CNN	ML(SVM)	EEG	96.44	98.92	93.16	ASD:61 & HC:61	10 FCV	Private
[82]	FFT and mRmR	ML(SVM)	EEG	68			ASD:49 & HC:48	–	Private
			ET	72.33					
			Fused	85.44					
[145]	Visibility graph	ML(SVM)	EEG	94.16	97.87	92.76	ASD:28 & HC:28	10 FCV	Private
[146]	Linear & nonlinear	ML(SVM)	EEG	90.57	99.91		ASD:34 & HC:11	10 FCV	Private
[147]	Filtering	DL(LSTM)	EEG	93.27			ASD:08 & HC:05	holdout	Private
[91]	EMD	ML(ANN)	EEG	97.2	100	94.7	ASD:18 & HC:18	holdout	Private
[148]	ICA	DL(CNN)	EEG	80			ASD:40 & HC:48	LOSO	Private
[149]	Quantitative features	ML(ANN)	EEG	100	100	100	ASD:15 & HC:10	10 FCV	Private
[150]	SPP and coherence	SA	EEG				ASD:27 & HC:24	–	Private
[98]	CC and entropy	SA	EEG				ASD:16 & HC:16	–	Private
[151]	GIC	SA	EEG				ASD:09 & HC:08	–	Private
[84]	FFT	ML(FLD)	EEG	80.27			ASD:08 & HC:10	LOSO	Public
[152]	CWT and BFC	ML(SVM)	EEG	94.7	85.7	100	ASD:12 & HC:12	10 FCV	Private
[99]	EMD and SODP	ML(ANN)	EEG	94.44	100	88.89	ASD:60 & HC:60	–	Private
[100]	Entropy	ML(SVM)	EEG	91.38			ASD:52 & HC:52	holdout	Private

Table A.6
Summary of the ADHD detection in children studies included in the review.

Ref.	SP Method	Prediction	Modality	ACC	SEN	SPE	Subjects	Strategy	Dataset access
[85]	FFT & PSD	ML(SVM)	EEG	71.67			ADHD:30 & HC:30	10 FCV	Private
		DL(LSTM)		77.67					
[153]	Nonlinear features	ML(SVM)	EEG	97.5	97.2	96.9	ADHD:30 & HC:30	10 FCV	Public
[154]	Nonlinear features	ML(MLP)	EEG	93.65			ADHD:30 & HC:30	Holdout	Public
[86]	Spectral analysis with FFT	ML(SVM)	EEG	72.7			ADHD1:54 & ADHD2:53 & HC:54	5 FCV	Private
[155]	STD & MSE	SA	EEG				ADHD:25 & HC:25	–	Private
[156]	Quantitative features	ML(RF)	EEG	81.82			ADHD:61 & HC:60	5 FCV	Public
[157]	SL & WC	DL(CNN)	EEG	98.85		99.25	ADHD:61 & HC:60	5 FCV	Public
				99.17		100		SB	
[7]	VMD & HT	ML(ELM)	EEG	99.95	100	99.89	ADHD:61 & HC:60	10 FCV	Public
[158]	PCC	DL(LSTM)	EEG	99.75		99.74	ADHD:46 & HC:45	5 FCV	Public
[87]	PSD	SA	EEG				ADHD:42 & HC:31	–	Private
[159]	Filtering	DL(LSTM)	EEG	94.25			ADHD:12 & HC:12	Holdout	Private
[160]	ECP	ML(ANN)	EEG	99.09			ADHD:61 & HC:60	10 FCV	Public
[161]	SWT	SA	EEG				ADHD:61 & HC:60	–	Public
[162]	ECV	ML(ANN)	EEG	89.1			ADHD:61 & HC:60	Holdout	Public
[163]	STFT & spectrogram	SA	EEG				ADHD:29 & HC:20	–	Private
[164]	Filtering	DL(CNN)	EEG	99.46	99.45		ADHD1:12 & ADHD2:13 & HC:14	5 FCV	Private
[165]	Nonlinear features	ML(KNN)	EEG	83.33	83.78	82.86	ADHD:46 & HC:45	Holdout	Public
[166]	CWT	ML(SVM)	EEG	94.74			ADHD:09 & HC:10	FCV	Private
[167]	DFT	SA	EEG				ADHD:04 & HC:03	–	Private
[40]	LZC	ML(NB)	EEG	79.54	82.6	80.95	ADHD:23 & HC:21	LOSO	Private
			fNIRS	77.27	73.91	71.42			
			Fused	93.18	95.65	90.47			
[94]	WPD & TQWT	ML(KNN)	EEG	97.19	97.12		ADHD:61 & HC:60	10 FCV	
				87.6	87.62			LOSO	Public
[168]	RQA	DL(CNN)	EEG	77.78	88.89		ADHD:22 & HC:22	Holdout	Private
[88]	PSD	DL(CNN)	EEG	90.29			ADHD:50 & HC:57	Holdout	Private
		ML(SVM)		87.9					
[61]	Topographic maps	DL(EEGNet)	EEG	83			ADHD:100 & HC:44	LOSO	Public
[169]	Connectivity matrix	DL(CNN)	EEG	92.06			ADHD:50 & HC:57	10 FCV	Private
		ML(SVM)		84.17					
[44]	EMD & DWT	ML(KNN)	EEG	94.74	91.75	100	ADHD:45 & ADHD+CD:62 & CD:16	3 FCV	Private
				97.88	96.68	100		10 FCV	
[101]	DWT & nonlinear features	ML(MLP)	EEG	91.3	91	91	ADHD:23 & HC:23	LOSO	Private
[170]	PCA	ML(KNN)	EEG	86	78		ADHD:77 & HC:80	LOSO	Private
[89]	PSD & Spectral entropy	DL(LSTM)	EEG	92.15	90.95	93.43	ADHD:08 & HC:08	Holdout	Private
		ML(SVM)		88					

Table A.7
Summary of the SZ detection in children studies included in the review.

Ref.	SP Method	Prediction	Modality	ACC	SEN	SPE	Subjects	Strategy	Dataset Access
[171]	VAR & PDC	ML(SVM)	EEG	90.37	91.11	89.64	SZ:45 & HC:39	5 FCV	
		DL(CNN)		91.69	91.11	92.5		5 FCV	Public
[172]	Filtering	SA	EEG				SZ:14 & HC:22	–	Private
[173]	Filtering	SA	MEG				SZ:15 & HC:14 & CD:16	–	Private
[174]	VAR & PDC	ML(DBN)	EEG	95			SZ:45 & HC:39	Holdout	Public
[175]	Handcrafted features	ML(DT)	EEG	44.75			SZ:65 & HC:40	5 FCV	Private
	Raw EEG	DL(LSTM)		69.8	68.29	80.09			
[176]	Power spectrum	SA	EEG	80	76	85	SZ:45 & HC:39	–	Public
[177]	STFT & Spectro-gram	DL(VGG16)	EEG	95		95	SZ:45 & HC:39	Holdout	Public
[90]	FFT & STFT	ML(SVM)	EEG	66	69	63	SZ:45 & HC:39	10 FCV	Public
		DL(SNN)		95	98	92			
[178]	PCC	DL(CNN)	EEG	90	90	90	SZ:45 & HC:39	Holdout	Public
[107]	CWT	DL(CNN)	EEG	98			SZ:45 & HC:39	Holdout	Public
[179]	Nonlinear features	SA	EEG				SZ:45 & HC:39	–	Public
[180]	Local binary pattern	DL(CNN)	EEG	97.7			SZ:45 & HC:39	Holdout	Public
[102]	Entropy	SA	EEG				SZ:45 & HC:39	–	Public
[62]	Handcrafted features	ML(DT)	EEG	96.7			SZ:45 & HC:39	Holdout	Public
	CWT+CNN	ML(DT)		98.3					
[181]	Finite differences	ML(RF)	EEG	84.5			SZ:45 & HC:39	10 FCV	Public
[92]	EMD	DL(CNN)	EEG	96.02	96		SZ:45 & HC:39	5 FCV	Public
[182]	Collatz pattern	ML(KNN)	2021	93.58	95.79	90.24	SZ:45 & HC:39	10 FCV	Public

Table A.8
Summary of the Dyslexia detection in children studies included in the review.

Ref.	SP Method	Prediction	Modality	ACC	SEN	SPE	Subjects	Strategy	Dataset access
[103]	Entropy	SA	EEG				DYS:16 & HC:20	–	Private
[183]	WPD	SA	EEG				DYS:15 & HC:15	–	Private
[16]	Nonlinear feature	ML(SVM)	EEG	72.9	72.3	74.7	DYS:16 & HC:32	5 FCV	Private
[184]	PRNCC	ML(LR)	EEG	AUC 79			DYS:45 & HC:45	LOSO	Private

(continued on next page)

Table A.8 (*continued*).

Ref.	SP Method	Prediction	Modality	ACC	SEN	SPE	Subjects	Strategy	Dataset access
[185]	DFT	ML(SVM)	EEG	76.2	55.9	83.5	DYS:16 & HC:32	5 FCV	Private
[186]	Connectivity features	ML(SVM)	EEG	72.8	66.7	78.9	DYS:16 & HC:32	LOSO	Private
[63]	Functional connectivity	ML(SVM)	EEG	95.34	96.42	93.33	DYS:29 & HC:15	LOSO	Private
[187]	SSA	DL(1D CNN)	EEG	65	67	55	DYS:16 & HC:32	–	Private
[96]	DWT	ML(KNN)	EEG	75			DYS:11 & HC:10	Hold out	Private
[93]	EMD & entropy	ML(SVM)	EEG	92			DYS:16	LOSO	Private
[188]	WPD	SA	EEG				DYS:15 & HC:15	–	Private
[189]	Filtering	ML(SVM) DL(CNN)	EEG	AUC 95 AUC 87			DYS:95	5 FCV	Private
[190]	Filtering	ML(KNN)	EOG	73.61	86.7	61.16	DYS:10 & HC:10	5 FCV	Private

Table A.9
Summary of the Depression detection in children studies included in the review.

Ref.	SP Method	Prediction	Modalities	ACC	SEN	SPE	Subjects	Strategy	Dataset access
[66]	Nonlinear features	ML(SVM)	EEG	81.03			DEP:20 & HC:19	LOSO	Private
			EM	80.17					
			Fused	83.42					
[41]	Linear & nonlinear features	ML(SVM)	EEG	73.53	76.43	71.8	DEP:81 & HC:89	5 FCV	Private
	Prosodic features		Vocal	74.12	74.89	72.07			
			Both	76.4	70.78	81.52			
[38]	EMD	SA	EEG, ECG, EMG				–	–	–
[64]	MPWD	DL(CNN)	EEG	97.27	97.22	97.35	DEP:34 & HC:30	10 FCV	Public
[14]	Physical features	SA	ECG				Total: 98	–	Private
[39]	Filtering	SA	ECG, EMG, HR, SPO2				Total: 3	–	Private
[67]	Power & phase features	ML(SVM)	EEG	79.45	81	78	Total: 22	10 FCV	Private
	HRV		ECG	–	–	–			
[68]	FFT	SA	EEG				DEP:80 & HC:173	–	Private
[65]	ICA	DL(CNN)	EEG	99.37	99.1		DEP:18 & HC:15	Hold out	Private
				91.4	88.7			10 FCV	

Table A.10
Summary of the anxiety detection in children studies included in the review.

Ref.	SP Method	Prediction	Modality	ACC	SEN	SPE	Subjects	Strategy	Dataset access
[191]	–	SA	PSG				ANX:15 & HC:15	–	Private
[69]	PSD	ML(SVM)	EEG	57.47			ANX:45 & HC:47	FCV	Public
			EM	51.13					
			Fused	82.7	81.88	83.04			
[83]	FFT	SA	EEG				ANX:15 & HC:5	–	Private
[192]	HRV	SA	ECG				ANX:30 & HC:30	–	Private
[11]	Filtering	SA	EEG				Total:152	–	Private
[116]	DFT	SA	EEG ECG				Total:10	–	Private
[12]	ERP	SA	EEG				Total: 25	–	Private

Table A.11
Summary of the post-traumatic stress disorder in children studies included in the review.

Ref.	SP Method	Prediction	Modality	ACC	SEN	SPE	Subjects	Strategy	Dataset access
[17]	–	SA	EEG				PTSD:23 & HC:23	–	Private
[193]	Partial connectivity	ML(SVM)	MEG	AUC 90			PTSD:23 & HC:21	10 FCV	Private
[70]	PCC	ML(SVM)	fMRI	95.2			PTSD:14 & HC:14	Hold out	Private
[71]	Prosodic	ML(XGBoost)	Speech	98.25			Total:200	Hold out	Private

Table A.12
Summary of the Tourette syndrome in children studies included in the review.

Ref.	SP Method	Prediction	Modality	ACC	SEN	SPE	Subjects	Strategy	Dataset access
[20]	ERP	SA	EEG				TS:18 & HC:20	–	Private
[22]	visual features	DL(LSTM)	EEG	94.87	78.78		TS:68	3 FCV	Private
[194]	Coherence	SA	EEG				TS:16 & HC:16	–	Private
[72]	Filtering	DL(CNN)	EEG	65	48	82	TS:25 & HC:25	Hold out	Private

Table A.13
Summary of the Obsessive–compulsive disorder in children studies included in the review.

Ref.	SP Method	Prediction	Modality	ACC	SEN	SPE	Dataset	Strategy	Dataset access
[23]	Filtering	SA	EEG				OCD:96 & HC:27	–	Private
[73]	Entropy	ML(SVM)	EEG	85	85.22	84.78	Total:10	2 FCV	Private
[195]	Relative power	ML(SVM)	EEG	81.04	82.05		OCD:39 & HC:40	10 FCV	Private

Table B.14
Abbreviations used in the review method.

A
Accuracy (ACC)
Anxiety (ANX)
Area under the curve (AUC)
Artificial neural network (ANN)
Attention deficit hyperactivity disorder (ADHD)
Autism spectrum disorder (ASD)
Autoencoder (AE)
B
Brain connectivity features (BFC)
C
Convolutional neural network (CNN)
Continuous wavelet transform (CWT)
Correlation coefficient (CC)
D
Decision tree (DT)
Deep belief network (DBN)
Deep learning (DL)
Depression (DEP)
Discrete Fourier transform (DFT)
Discrete wavelet transform (DWT)
Dyslexia (DYS)
E
Effective connectivity patterns (ECP)
Effective Connectivity Vector (ECV)
Empirical mode decomposition (EMD)
Electrocardiogram (ECG)
Electroencephalogram (EEG)
Electromyogram (EMG)
Electrooculogram (EOG)
Extreme learning machine (ELM)
Event related potential (ERP)
Eye tracking (ET)
F
Fast Fourier transform (FFT)
Fisher Linear Discriminant (FLD)
Fold cross validation (FCV)
Functional near-infrared spectroscopy (fNIRS)
G
Graph Index Complexity (GIC)
H
Heart rate (HR)
Heart rate variability (HRV)
Healthy control (HC)
Higher order spectra (HOS)
Hilbert transform (HT)
I
Independent component analysis (ICA)
K
K-nearest neighbor (KNN)
L
Leave one subject out (LOSO)
Lempel Ziv complexity (LZC)
Logistic regression (LR)
Long short term memory (LSTM)
M
Machine learning (ML)
Magnetoencephalogram (MEG)
Maximum Relevance Minimum Redundancy (mRmR)
Mental health (MH)
Modified multiscale entropy (mMSE)
Multilayer perceptron model (MLP)
Multiscale entropy (MSE)
Multivariate pseudo Wigner distribution (MPWD)

(*continued on next page*)

Table B.14 (*continued*).

N
Naive bayes (NB)
O
Obsessive–Compulsive Disorder (OCD)
P
Partial directed coherence (PDC)
Phoneme-Related Neural-Congruency Components (PRNCC)
Post-Traumatic Stress Disorder (PTSD)
Power spectral density (PSD)
Probabilistic neural network (PNN)
Principle component analysis (PCA)
S
Schizophrenia (SZ)
Second-order difference plot (SODP)
Sensitivity (SEN)
Short-time Fourier transform (STFT)
Siamese neural network (SNN)
Singular Spectrum Analysis (SSA)
Singular value decomposition (SVD)
Specificity (SPE)
Spectral power (SPP)
Standard deviation (STD)
Stationary wavelet transform (SWT)
Statistical analysis (SA)
Support vector machine (SVM)
SqueezeNet (SQZN)
Synchronization likelihood (SL)
R
Recurrent quantification analysis (RQA)
Random forest (RF)
ResNet (RSN)
T
Thresholding (THLD)
Time–frequency representation (TFR)
Tourette Syndrome (TS)
Tunable Q wavelet transform (TQWT)
V
Variational mode decomposition (VMD)
vector autoregressive (VAR)
W
Wavelet coherence (WC)
Wavelet packet decomposition (WPD)
Wavelet transform (WT)

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