Review Article

Investigation of Machine Learning Methods for Early Prediction of Neurodevelopmental Disorders in Children

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Several variables, for instance, inheritance and surroundings, influence the growth of neurodevelopmental disorders, e.g., autism spectrum disorder (ASD) and attention deficit hyperactivity disorder (ADHD) during the first 36 months of life [1]. ADHD is the most predominant childhood disorder initially characterized by behavior issues [2, 3]. In addition, ADHD is a multisystemic neurodevelopmental condition which is linked to temporal, operational, and structural connectivity impairments in the temporoparietal, front striatal, and frontal cortex networks [4–6]. ASD, like ADHD, is also initially characterized by inappropriate behavior [7], including spatial memory difficulties [8].

1. Introduction

There are several variables, for example, inheritance and surroundings, which influence the growth of neurodevelopmental disorder such as autism spectrum disorder (ASD) and attention deficit hyperactivity disorder (ADHD) during the first 36 months of life [1]. ADHD is the most predominant childhood disorder initially characterized by behavior issues [2, 3]. In addition, ADHD is a multisystemic neurodevelopmental condition which is linked to temporal, operational, and structural connectivity impairments in the temporoparietal, front striatal, and frontal cortex networks [4–6]. ASD, like ADHD, is also initially characterized by inappropriate behavior [7], including spatial memory difficulties [8].

The issues faced by children having ASD and ADHD are shown in Figure 1. Both conditions appear at a young age and can last throughout adulthood, causing multiple disabilities as well as significant burdens on individuals and families [9]. Even though the first tools for diagnosing mental problems were developed in the late 1800s [10], ADHD and ASD diagnosis primarily relies heavily on traditional clinical assessments from the last few decades, as described in Figure 2. For example, a study was conducted [11, 12] in which the population size was around 300 school children. In this study, it was concluded that neuropsychological testing using virtual reality has better ecological validity than traditional CPT (Continuous Performance Test) while differentiating children with ADHD from healthy controls. Most traditional methods are based on massive data...
collection from multiple respondents’ replies and the extent of various behavioral descriptors, which is then recognized by the researcher while forming a diagnostic criterion [13, 14]. In order to find relevant information, a range of techniques have been used, from subjective (e.g., Likert scale) and unstructured clinical assessments to more precise (observation method) and structured (standard diagnostic interview sessions) methods. However, the possibility of being misdiagnosed is very high, with an estimated 20 percent misinterpretation rate in the United States [15, 16]. Mostly misdiagnosed leads to the administration of unnecessary long-term pharmaceutical treatment, which causes a reduction in functioning and increases the risk of development of additional social and clinical issues [17]. Moreover, such diagnostic procedures are also time-consuming and costly. In most cases, early assessment for ASD and ADHS in children is mainly done by families, instructors, and others with no special training or skills. Even though diagnostic and statistical manuals for mental disorders are available and are used by the physician, they are still not sufficient for rapid diagnosis of both conditions [18, 19]. Despite this, neuroimaging studies have confirmed persistent structural and functional brain alterations associated with ADHD and ASD, leading to reconsideration using new diagnostic methods [20–22]. In this sense, rapid and advanced criteria are required to be accurate and cost-effective.

Machine learning (ML) and deep learning (DL) are the subfields of artificial intelligence (AI). Deep learning has evolved faster in the last few years. It is an advanced phase of Machine learning with a vast application from defense to marketing. Deep learning presents healthcare with groundbreaking applications. The primary strength of DL lies in gathering a massive amount of data. It applies its advanced neural networks to come up with its best outcome. Medical professionals and researchers can leverage DL to discover the hidden possibilities in data. Some examples of applications of DL in healthcare include remote patient monitoring, genome sequencing, medical imaging, drug discovery, detection of medical insurance fraud, and personalized treatment. It can also be used as a computational approach in neurobiology. This is evidenced by extensive effort in establishing ML algorithms and deep learning (DL) approaches to interpret elevated magnetic resonance imaging (MRI) data to neural network models that regulate the brains of people with all sorts of psychological disorders [23]. Therefore, this study emphasizes on the use of ML techniques for the early detection and treatment of symptoms related to ADHD and ASD.

In this review, Google Scholar, Science Direct, and PubMed databases were used to acquire the paper’s prediction of neurodevelopmental disorders in children using machine learning methods. As PubMed and Science Direct are commonly referred libraries that contain articles that are highly cited by most of the researchers in the field of health science. The keywords used for the search string are (“autism spectrum disorder,” “ASD,” “attention deficit
hyperactivity disorder,” “ADHD”) AND “machine learning” to select the papers. For clear visualization, these phrases were also searched on the internet. The range of the publication’s year was set between 2017 and 2022. In order to identify some specific sources for systematic reviews and studies, some manual searches (checking the reference list of primary studies) were also done. Figure 3 shows the number of articles identified through different databases. Furthermore, we were able to find more relevant studies by the reference list of primary studies. Table 1 shows the inclusion and exclusion criteria used in this study to complete the article selection process.

The outline of the paper is as follows: in Section 2, we discuss the recent state-of-the-art ML and DL models proposed for ADHD and ASD detection along with medical imaging techniques used in diagnosis. In Section 3, a thorough discussion and comparison of the gathered results are presented, and finally, paper concludes in Section 4.

2. Machine Learning and Deep Learning Methods Proposed for ADHD and ASD Detection

ML is a rapidly expanding field of examination that is aimed at creating excellent prediction models through search strategies, DL, and computational analysis. These are computer-assisted data processing systems that do not require much human participation. ML approaches include decision trees, neural networks, rule-based classifiers, and support vector machines. In specific ways, ML is seen as a possible substitute to undertaking inductive and presumption exploratory data analysis [24, 25]. ML is a collection of analytical techniques that learn from data distributions to make judgments based on fresh data. It is utilized to create sophisticated apps that generate accurate classifications and predictions on a wide range of data [26]. Therefore, in both ophthalmic data analysis and other fields, ML has been widely used [27].

2.1. Medical Imaging Techniques Used in the Diagnosis of ASD/ADHD

2.1.1. Magnetic Resonance Imaging (MRI). MRI became available in the 1990s, allowing researchers to investigate neural activity without having patients endure intravenous fluids, surgeries, and toxin medications or to face radionuclides. ML when applied on MRI images is found to be more accurate than other quantitative approaches, for instance continuous, quality evaluations [28, 29]. As a result, structural (s) MRI and functional (f) MRI have made substantial progress in finding potential ASD and ADHD biomarkers in patients. Even though ADHD is not linked with large morphological alteration in the brain, MRI imaging can detect tiny structural variations in the brain of ADHD patients [30, 31]. Therefore, it is observed that in the recent search for biomarkers of neurological and psychiatric disorders such as ADHD, deep learning when applied to resting state functional MRI data could be a powerful tool [32, 33]. Moreover, when neuroanatomical data from control (normal individuals) and ADHD participants were compared, it was discovered that the ADHD patient’s brains had smaller

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**Figure 3:** Publications identified through different databases between the 2017 and 2022 periods.

**Table 1:** Criteria for determining which studies should be included and which should be excluded from the study.

<table>
<thead>
<tr>
<th>Inclusion criteria</th>
<th>Exclusion criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>English language articles</td>
<td>Not in the English language</td>
</tr>
<tr>
<td>Studies of original articles, case reports, and review</td>
<td>Duplicate titles</td>
</tr>
<tr>
<td>Articles published between 2017 and 2022</td>
<td>Articles that include other studies</td>
</tr>
<tr>
<td>Articles related to ADHD and ADS with ML</td>
<td>Research related to ADS</td>
</tr>
<tr>
<td>Research related to ADS</td>
<td>Research related to ADHD</td>
</tr>
</tbody>
</table>

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Incorporated Adamax optimization technique and reported on an ASD diagnosis model based on resting-state MRI data of children from the age of 5 to 10 years, from global ABIDE I and ABIDE II datasets. They assessed the regional average cortical thickness of brain areas surrounding the prefrontal-striatal region. Furthermore, some studies extended this finding to provide the dorsolateral prefrontal cortex, orbitofrontal [34, 35], and the ventral tegmental area, which is part of the reward circuit [36].

Likewise, the identification of ADHD in adults has recently become a source of debate. Therefore, Chaim-Avancini et al. [37] established a classification method based on diffusion tensor imaging (DTI) and structural MRI data, for the first time, in stimulant-naïve adults. The diagnostic accuracy values and area-under-the-curve (AUC) for ADHD subgroups (mixed-gender) and separately matched healthy controls (HC) \(n = 58\) each were up to 0.71 and 66 percent \(P = 0.003\), respectively. However, when studies were limited to males, the AUC \(n = 52\) and diagnostic accuracy values inclined to 0.74 and 74 percent \(P = 0.0001\), correspondingly. A similar study was proposed, which specifies that MRI-based evaluations are a promising approach for the biomarker improvement of ADHD in children and young adults [38]. In addition, using 3D convolutional neural networks (CNNs) and MRI images, Zou et al. [39] constructed a DL-based ADHD classification technique. They recommended extracting of significant 3D low-level characteristics from fMRI and MRI data for the first time. They also created a 3D CNN model to look at MRI features and local spatial patterns. They established that structural and functional knowledge about the brain is compatible. Therefore, they built multimodality CNN architecture that includes a combination of MRI and fMRI characteristics. Based on the hold-out testing statistics from the ADHD-200, the suggested 3D CNN multimodality method achieved an accuracy of 69.15 percent.

In another experimental investigation by Zao et al. [40], the combination of both low and first-level high-order functional connectivity (FC) networks yields the diagnostic accuracy of up to 81 percent for ASD. The authors noted that high-order FC traits could contribute extra details to low-order FC features in ASD diagnosis. They gathered data between any two brain areas of interest by calculating FC using Pearson’s correlation between rs-fMRI time series (ROIs). Similarly, in another study [41], the authors combined R-fMRI data with ML algorithms to increase ASD diagnosis, predict clinical phenotypes, and provide more targeted therapies. Khundrakpam et al. [42] conducted a brain imaging data exchange study on 1100 people aged between 6 and 55 years. Their findings support the theory that cortical thickness anomalies reflect late maturation and emphasize the ASD nature of morphological abnormalities. A predictive diagnosis model is presented in [43]. The model was trained on the data collected from 46 children suffering from ASD and 39 with other developmental delays. In this study, they assessed the regional average cortical thickness of brain areas using the top 20 most important random forest classifiers (aged 18 to 37 months). In another study [44], the authors gathered data of children from the age of 5 to 10 years, from global ABIDE I and ABIDE II datasets. They proposed an ASD diagnosis model based on resting-state (rs) fMRI data using CNNs. In the proposed model, they incorporated Adamax optimization technique and reported that their model has attained the accuracy 70%. They also reported that the proposed model can be used to analyze rs-fMRI data connected to other brain dysfunctions.

For the first time, there has been a study conducted on unsupervised data [45], which focuses on the high-order connectomes manifold learning for ASD detection via morphological brain networks. This study has used T1-w MRI scans and has achieved 61.69% accuracy.

Moreover, many other types of research have shown that automatic diagnosis increases accuracy in ASD with the help of MRI and fMRI [46]. Using functional connectivity and structural texture data obtained from 3D MRI and 4D fMRI scans of patients, a novel model to diagnose ADHD and ASD was proposed by Sen et al. [47]. Furthermore, multiple new data-sharing models based on MRI data can be used to overcome challenges associated with traditional clinical diagnoses for ADHD and ASD, as concluded by previously described reviews [48, 49].

2.1.2. Infrared Spectroscopy (IR). Using near-infrared spectroscopy (nIRS) for functional brain imaging, a categorization model was tested in medicated-naïve and methylphenidate-administered ADHD and ASD comorbid ADHD children. According to the findings, methylphenidate increased activity in the right hemisphere towards the midline vertex in patients significantly. Moreover, activation of oxygenated-hemoglobin concentration changes in the angular, right middle frontal, and precentral gyri under methylphenidate treatment resulted in 86.1%, 93.3%, and 82.6% specificity, sensitivity, and accuracy. Thus, the significantly distinct methylphenidate triggered response might be helpful tools for differentiated diagnostic analyses [50]. Other findings showed that data from far (f) NIRS and EEG could be used to enhance classification accuracy. The result has demonstrated that healthy subjects showed higher right prefrontal activation than ADHD children, according to fNIRS. Moreover, using EEG and EEG-fNIRS systems, ML approaches, such as Naïve Bayes, produced the best diagnosis with 79.54 percent and 93.18 percent accuracy rates, respectively [51]. Similarly, many studies were conducted using IRS to improve the diagnosis and study brain function of ASD and ADHD patients and patients with other psychological disorders [52–55]. A meta-analysis on fMRI was performed with 6–16-year-old participants to see how well these research results aligned in the setting of executive function (EF) impairment in ADHD. The qualitative examination on fNIRS datasets reveals continuous hypoactivity in the right prefrontal cortex in numerous EF activities. Moreover, in contrast to controls, alter activity in the region and surrounding areas during EF tasks in ADHD was observed. These findings suggest using fNIRS brain images to study cortical activity changes in ADHD [56].

On the other hand, Kuwabara et al. [57] reported the first investigation on ASD brain functioning using fNIRS in 2006. Since then, IRS has been used in several research studies because it has multiple benefits over the other neuroimaging methods for studying ASD brain functions. This benefit primarily includes low cost, portability, and usability in realistic settings [57]. Dozens of empirical studies...
available in the last decade that employed fNIRS in people with ASD or children at significantly higher risk of ASD have been studied by Zhang et al. This research looked at brain activation in ASD using a range of functions (e.g., joint attention, facial processing, and working memory) as well as a structural unit in a resting-state condition. In the majority of these research, atypical brain activation was found in superior and middle temporal gyrus, inferior frontal gyrus, and the prefrontal cortex.

Moreover, functional connectivity was shown to be changed during resting-state, implying that in ASD, information transmission across brain regions is inefficient. Overall, their review shows that fNIRS is a potential method for studying neurodevelopment in children with ASD starting at a young age [58]. Even though research based on demographic classification is lacking, a study suggests that ASD has reduced prefrontal hemodynamic responses when studied with nIRs in male children [59].

2.2. Deep Learning Techniques Used for ADS and ADHD.

Deep learning is the process of using AI to train and test a multilayered neural network to understand complex structures and concepts [32]. In contrast to DL, traditional ML approaches use various extracting features and classification methods, but with DL, feature extraction and classification are done comprehensively. Therefore, the majority of ADHD and ASD diagnosis methods focus on DL techniques based on neuroimaging approaches [60]. Using the DL algorithm, researchers achieved a different pattern between ASD and normal youngsters using an electroencephalogram (EEG) [61]. A similar approach was applied by merging an EEG-based brain network with CNN to suggest a DL framework for ADHD diagnosis, specifically in children. The proposed framework performed admirably, with an accuracy of 94.67 percent [62].

Furthermore, using DL with EEG, many other researchers have reported ADHD diagnosis in children as well as adults [62–65]. Another study examined ASD using diverse models (n = 14) (i.e., recurrent neural and convolutional networks). By means of an open-source ASD MRI scan dataset (n = 1000) and a higher resolution structural MRI dataset, researchers established how deep neural networks may have been utilized to detect and investigate psychiatric illnesses. They discovered that subcortical structures, such as the basal ganglia, are related to structural and strategic signals [66]. In addition, by using deep ML, the researcher could also identify and pinpoint the areas of the brain that contributed the most to differentiating ASD from controls. From the ABIDE dataset, their technique identified ASD patients with 70% accuracy compared to control patients [67].

2.2.1. DL API (Application Programming Interface).

The use of machine learning to generalize categorization in the field of neuroimaging is gaining popularity. Therefore, a significant amount of research has been conducted on diagnostic models for neurodevelopmental disorders using MRI, fNIRS, and other techniques. In this regard, a comprehensive review was provided by Gautam et al. [68] on DL strategies used in the prognosis of eight neurological disorders and neuropsychiatric together with Alzheimer’s disease, epilepsy, stroke, migraine, autism, Parkinson’s disease, cerebral palsy, and multiple sclerosis. The authors have examined a total of 136 articles (n = 136) that dealt with neurological and neuropsychiatric illnesses that were diagnosed using various DL techniques. Their findings show that multiple DL models can be used to diagnose migraine, cerebral palsy, and stroke more effectively. They also suggest that the performance of the restricted Boltzmann machine, deep belief network, and deep Boltzmann machine can be used and researched for the analysis of various human neuropsychiatric and neurological disorders.

In another review [69], comprehensive studies were led in the areas of DL-based rehabilitation tools and ASD diagnostic CAD systems. From this study, it was concluded that the Keras toolbox was used in most investigations, as Keras tool is considered high-level Application Programming Interface (APIs) which makes design more straightforward and the performance of this tool is stable due to sophisticated back ends like TensorFlow. Furthermore, this study also highlighted that the CNN was found to be the most popular DL network used for ASD detection. Also, the Softmax approach was discovered to be one of the best and most extensively used classifiers, as it differs across the entire domain and is less expensive.

2.3. Recent Machine Learning and Deep Learning Software Toolkits Used in ASD and ADHD Diagnosis.

The existence of numerous ML toolkits, including CNN, TensorFlow, and OpenCV in combination with hardware technologies, has resulted in a one-of-a-kind opportunity for researchers to regulate ML algorithms. Therefore, Liu et al. proposed a first DL method for classifying ADHD with single-nucleotide polymorphism (SNP) data. They utilized CNN to categorize individuals with ADHD from HC (healthy controls) by genomic data by taking SNP loci, i.e., 764 loci, as an input to achieve a 0.9018 accuracy, 0.9570 AUC, 0.8980 sensitivity, and 0.9055 specificities. Moreover, through saliency examination for the DL network, 96 genes were found to be related to ADHD, out of which 14 genes are documented in previous investigations. Likewise, their analyses recognized a potential risk of gene EPHA5 with a variant of rs4860671 in ADHD patients [60].

Additionally, an artificial recurrent neural network for action identification in-home therapy, cost-effective motion capture, and virtual reality game technology was built to capture different motions of ASD children. TensorFlow Sharp (TensorFlow 1.13) was used as a wrapper to build the recurrent neural network for the action recognition network in Unity. Keras, a high-level wrapper for TensorFlow, has designed and trained neural networks. In another method using data set from ABIDE I and II, 63.4% and 87.0% accuracy was achieved in ASD diagnosis when CNN-VGG-16 and ResNet-50 were used, and TensorFlow was applied for the dataset framework [70]. Similarly, using the ABIDE dataset, which was based on rs-fMRI and deep neural network, ASD was distinguished from typically developing subjects [71].
In addition, it was found that the CNN algorithm was most efficient among all applied ML algorithms, and several studies have reported the rise in accuracy for ADHD diagnosis and examination by utilizing CNN with an accuracy range of between 90 ± 10 percent [55, 72–78]. Similarly, numerous studies were also conducted using CNN for ASD diagnosis and analyses showing a high accuracy rate >70-90% [44, 79–82]. Furthermore, a hybrid two-stage network was constructed by combining a separated channel (SC)-CNN with attention (SC-CNN) to distinguish ADHD from HC with an accuracy of 68.6% [83]. Moreover, a high accuracy of 95.1% on a children dataset was recorded with a different camera (20 ms real-time response) by a gaze tracking system using a CNN algorithm. The images were extracted from one-minute stimulus videos. Another approach offered a promising solution by combining AI, ML, and medical robots and problem-specific algorithms in OpenCV. The strategy was developed to help children with ASD make eye contact [84]. Similarly, to ensure that the subject fully perceives, Waseda Anthropomorphic Saxophonist No.5’s facial expression, gaze detection is established through OpenCV and a USB camera. This study aims to improve ASD patient social skills with others more effectively [85].

3. Discussion

In this study we have provided a comprehensive overview of the investigations conducted in the scope of machine learning methods for early prediction of Neurodevelopmental disorders in children. Tables 2 and 3 represent the details of different methods proposed for Diagnosis of ADHD and ASD, respectively. Tables 2 and 3 provide the details of the methods/approaches in terms of methods they have used to achieve the results.

Table 2: Comparison of developed ML methods accuracy for the diagnosis of ADHD.

<table>
<thead>
<tr>
<th>Work</th>
<th>Disease</th>
<th>Methods</th>
<th>Number of participants (n)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>[37]</td>
<td>ADHD</td>
<td>ML-dependent pattern classification methods applied on diffusion tensor imaging (DTI) data and structural MRI</td>
<td>Mix gender</td>
<td>66</td>
</tr>
<tr>
<td>[38]</td>
<td>ADHD</td>
<td>Voxel-wise linear regression models were applied on MRI data</td>
<td>Male (n = 52)</td>
<td>74</td>
</tr>
<tr>
<td>[39]</td>
<td>ADHD</td>
<td>3D CNN applied to MRI scans</td>
<td>Young adults (n = 31)</td>
<td>83</td>
</tr>
<tr>
<td>[62]</td>
<td>ADHD</td>
<td>EEG-based brain network with CNN</td>
<td>Mix gender</td>
<td>69.15</td>
</tr>
<tr>
<td>[40]</td>
<td>ASD</td>
<td>Multilevel, high-order functional connectivity features through rs-fMRI scans</td>
<td>7–21 years old (n = 285)</td>
<td>94.67</td>
</tr>
<tr>
<td>[51]</td>
<td>ADHD</td>
<td>EEG-fNIRS systems Using Naïve Bayes</td>
<td>Male (n = 7)</td>
<td>81</td>
</tr>
<tr>
<td>[65]</td>
<td>ADHD</td>
<td>EEG-based data with CNN</td>
<td>Female (n = 7)</td>
<td>93.18</td>
</tr>
<tr>
<td>[72]</td>
<td>ADHD</td>
<td>CNN</td>
<td></td>
<td>90</td>
</tr>
<tr>
<td>[73]</td>
<td>ADHD</td>
<td>CNN</td>
<td></td>
<td>0.875</td>
</tr>
<tr>
<td>[74]</td>
<td>ADHD</td>
<td>DCNN derived from the time-frequency decomposition EEG, chiefly of event-related potentials during the flanker task</td>
<td>Adult (n = 20)</td>
<td>88</td>
</tr>
<tr>
<td>[75]</td>
<td>ADHD</td>
<td>rs-fMRI from ADHD database CNN and 2D CNN–LSTM</td>
<td></td>
<td>&gt;90</td>
</tr>
<tr>
<td>[76]</td>
<td>ADHD</td>
<td>CNN developed on extracted seed correlations from diverse default mode network regions</td>
<td></td>
<td>84</td>
</tr>
<tr>
<td>[77]</td>
<td>ADHD</td>
<td>FCNet consists of a CNN fMRI from ADHD database</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[78]</td>
<td>ADHD</td>
<td>EEG-based data with CNN</td>
<td>Children (n = 22)</td>
<td>98.48</td>
</tr>
<tr>
<td>[83]</td>
<td>ADHD</td>
<td>SC-CNN applied to fMRI</td>
<td>ABIDE database (n = 1019)</td>
<td>68.6</td>
</tr>
</tbody>
</table>

Table 3: Comparison of developed ML methods accuracy for the diagnosis of ASD.

<table>
<thead>
<tr>
<th>Work</th>
<th>Disease</th>
<th>Methods</th>
<th>Number of participants (n)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>[79]</td>
<td>ASD</td>
<td>CNN applied to fMRI</td>
<td>ABIDE database (n = 1,112)</td>
<td>80</td>
</tr>
<tr>
<td>[45]</td>
<td>ASD</td>
<td>T1-weighted MRI</td>
<td></td>
<td>61.69</td>
</tr>
<tr>
<td>[67]</td>
<td>ASD</td>
<td>MRI images from ABIDE</td>
<td>ABIDE database</td>
<td>70</td>
</tr>
<tr>
<td>[81]</td>
<td>ASD</td>
<td>sMRI data applied to CNN</td>
<td>ABIDE database</td>
<td>71.8</td>
</tr>
<tr>
<td>[82]</td>
<td>ASD</td>
<td>fMRI data applied to CNN</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[96]</td>
<td>ASD</td>
<td>Mobile web portal</td>
<td></td>
<td>94</td>
</tr>
<tr>
<td>[97]</td>
<td>ASD</td>
<td>Mobile web portal</td>
<td></td>
<td>92</td>
</tr>
</tbody>
</table>
incorporated, the population size, and the accuracy of the models used for ADHD and ASD. Figure 4 shows the accuracy of different methods used for diagnosis of ADHD and ASD, whereas Figure 5 shows the accuracy rate of methods that are used for diagnosis of both ADHD and ASD.

3.1. Comparison of Deep Learning Methods for ADHD and ASD Diagnosis. The use of neuroimaging and DL together is still an area that has to be approached cautiously. The first difficulty this field faces is overfitting. Overfitting is the failure to construct an acceptable algorithm due to the high generalization caused by adapting to different data sources [86, 87]. Moreover, when the study’s dataset is limited, the overestimation problem generates [88]. In addition, spatial transformation approaches have acquired importance in the automated diagnosis of ADHD and ASD and therefore have revolutionized generalization ability. However, they are occasionally unreliable due to a lack of generalization in datasets with high volatility and a small sample size. For example, Zhu et al. [89] used fMRI scans from 24 participants (12 TDC and 12 ADHD) to train a classifier based on Fisher-discriminant analysis (FDA) and obtained an 85 percent leave-one-out cross-validation accuracy. But the quantity of the samples used in these investigations is limited, which causes limiting in the generalizability of the results. As a result, as previously stated, a large-scale statistical exploratory prediction exercise on ADHD could yield multiple promising leads for future scientific research of the neurological basis of ADHD [90].

Furthermore, in supervised learning, an algorithm predicts a target (dependent) from the input variables. Otherwise, the target variable is classified as definite or

![Figure 4: Comparison of developed ML methods accuracy for diagnosis of (a) ADHD and (b) ASD. DTI: diffusion tensor imaging; MRI: magnetic resonance imaging; CNN: convolutional neural networks; EEG: electroencephalogram; IR: infrared spectroscopy.](image-url)
continuous. For example, Hyde et al. [91] exhibited various patterns for developing a supervised ML approach in ASD. They talked about how this strategy works with multidimensional, genetic, and diverse databases. On the other hand, Stevens et al. [92] used unsupervised ML to identify and assess behavioral characteristics in ASD by using Gaussian mixture models and hierarchical clustering. Through the indications and characteristics found, this study attempted to examine the behavioral aspects of ASD and analyses the therapy response. Thabtah et al. [93] looked at recent clinical and screening ML studies in ASD. The research revealed the limits of existing methodologies and the critical concerns that must be addressed. Data, diagnostic time, and feature selection technique, all of which were relevant to ML for ASD classification, were among the concerns. Jacob et al. [94], on the other hand, highlighted how a longitudinal model and computational analytics method might improve the inferential ability for detecting debilitation before it reaches official ASD diagnostic thresholds. In another study [95], the researchers look at supervised and unsupervised methods for diagnosing ASD neurodevelopmental heterogeneity. Moreover, DL has an ever-increasing influence on research fields like voice analysis and ASD classification. Tariq et al. [96] used ML to classify children’s home movies, claiming that their solution reduced ASD classification time. In their research, they used eight ML algorithms on one sixty-two home movies (length 2 min) for American children with and without ASD. The study’s goal was to see if ML algorithms could reliably identify ASD on a digital application, and it succeeded with a 92 percent accuracy rate. Using these techniques, their group also achieved an accuracy (AUC) and sensitivity of 76 percent for diagnosing ASD children from those patients who are expected to have other developmental delays. Similarly, accuracy (AUC) and sensitivity of 76 percent were also achieved for diagnosing atypical from developmentally delayed children. These findings support using a mobile video-based and ML-directed approach to detect autism in...
Bangladeshi children early and remotely. These findings point to the possibility of employing a mobile video-based and ML directed strategy to detect autism in Bangladeshi children early and remotely [97]. For the above discussion, it can be concluded that combining multimodal features provides the best-known classification accuracy for differentiating ADHD or ASD patients from healthy subjects, which opens the way for automated computer-aided diagnosis of other psychiatric illnesses also.

Furthermore, in this review, we have broadly classified machine learning techniques employed into two broad categories: traditional ML approaches and deep learning approaches as shown in Figure 6. It has been observed that traditional ML approaches works well as classifiers and decision tree can be used as a highly recommended method for differentiating affected and healthy individuals whereas deep learning approaches when applied to datasets such as different types of MRI and biomarkers such as EEG can be used as an effective diagnostic tool not just for ASD and ADHD but other psychiatric illness also.

4. Conclusions

This study discovers numerous uses of ML approaches in identifying and categorizing ASD and ADHD and their risks and benefits, based on a comprehensive evaluation and analysis of ongoing investigations. Our analysis shows that differences in methodology lead to the heterogeneity of results between investigations and achieve accuracy (Tables 2 and 3). Therefore, scientific investigations should consist of more samples and rely on a prolonged test set for estimating accuracy rate rather than cross-validations. Moreover, in unbalanced samples, % correct should never be used to measure accuracy for diagnosis of both ASD and ADHD conditions in future studies. Our findings also showed the significance of gathering data from less represented groups, notably women and adults. Furthermore, methods that can simultaneously diagnose both conditions with differentiation should be focused more (Figure 5). We hope that our assessment helps readers understand the work that has gone into developing ADHD and ASD diagnosis by using ML. When correct diagnosis can be obtained at an early stage of disorders, it can have huge impact on treatment. Results of these diagnosing methods have a vivid future prospect of applications in cyberphysical technology in the field of speech-language therapy. Thus, treating children in those part of the world where access to psychiatrists is difficult or scarce can be made possible.

Data Availability

Here is the link to publicly archived dataset analyzed and referred dataset, downloaded using guest ID-20220327_170948 ABIDE I-ixi Data (https://www.nitrc.org/ir/app/action/ProjectDownloadAction/project/ixi) and ABIDE II-MRI Data Quality Metrics (http://fcon_1000.projects.nitrc.org/indi/abide/abide_II.html)

Disclosure

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Conflicts of Interest

The authors declare no conflict of interest.

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