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Exploring Diverse Approaches for Detecting and Diagnosing Attention Deficit Hyperactivity Disorder: A Comprehensive Survey

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ABSTRACT

Impulsivity, hyperactivity, and inattentiveness are illnesses of the neurodevelopmental ailment known as attention deficit hyperactivity disorder (ADHD). Since the illness's public awareness has increased recently, it is considered a significant public health concern, so has the prevalence of diagnosis. One of the biggest challenges in treating ADHD is accurate diagnosis. Misdiagnosis has had negative effects on health. This condition is quite complicated, hence there isn't a computational expert system available for diagnosis. If left untreated, the psychiatric disorder known as ADHD may significantly affect a person's life in terms of their academic performance, social interactions, and psychiatric effects. Tools with high accuracy and objectivity must be created to classify ADHD. Deep learning analysis of brain signals for automated diagnosis of ADHD has drawn more interest recently. Given that Without requiring any radiation exposure, functional magnetic resonance imaging (fMRI) it has been implemented extensively in the research of brain cognition in recent years and has seen fast development. The creation of customized, trustworthy, and successful treatment regimens is hampered by a lack of knowledge about the underlying brain processes. There is reason that suggests that multivariate variables related to cognitive, genetic, and biological domains may be concurrently linked with ADHD, based on diverging and inconsistent results from existing studies. Compared to traditional statistical methods, deep learning and machine learning are two examples of artificial intelligence (AI) techniques that are more adept at recognizing complicated connections between several variables. This article offers a summary of techniques for identifying and diagnosing attention deficit hyperactivity disorder, or ADHD. The primary goal is to examine the many studies on ADHD to pinpoint any knowledge gaps. Several studies on the identification of ADHD by deep learning and image processing methods are covered in this survey. Lastly, an overview of ADHD detection methods is given in this article.

1. INTRODUCTION

Among the most common neuropsychiatric conditions, according to estimates, 5% of school-age children worldwide suffer from ADHD. In up to 65% of cases, the illness's symptoms remain into adulthood. A group of diseases known as ADHD are connected to several dysfunctions. The name of this condition consists of two words, each of which is linked to a different ADHD symptom. Those with attention deficit disorder in the first category find it difficult to concentrate on a single problem and are readily sidetracked by anything going on in their environment.

Conversely, the patients in the second group exhibit signs of hyperactivity, which means they can stand still for extended periods of time and are always moving and changing their posture. In certain cases, they even shout or quickly stop talking during a regular discussion. Children at varying stages of development may experience any one of these disorders [1].

A neurobehavioral condition with a high frequency in children, Excessive activity, difficulty concentrating, and other related neurobehavioral variations are symptoms of ADHD. In adulthood, 30 to 50 percent of kids at school who have ADHD still suffer from the disease. Approximately 5-7% of Children in school age have ADHD. It is critical to get the most precise diagnosis of this illness so that children who require therapy can receive it on time. depending on their age and gender, children with attention deficit disorder have varied effects, with boys being more likely to have it than girls. The earliest indications of hyperactivity are usually difficult to identify until the child becomes four, and they are most evident throughout elementary school. Yet, research shows that the primary features of ADHD vary with age, suggesting that ADHD appears to decrease in adulthood regardless of categorization. Hyperactivity is less evident across this age range even if it is still there for treatment. As a result, to diagnose ADHD and identify certain symptoms, an extensive medical record is needed.

Forgetfulness, disorganization, and trouble completing activities are some of the symptoms associated with ADHD, and a lack of focus and organisation. In addition, people with

ADHD struggle to make decision-making skills and lack emotional control, which has a negative effect on several areas of life, such as relationships with others, employment, and academics. As a result, for early treatment and management of ADHD, an early diagnosis is necessary, to enhance the results for those suffering from ADHD and to stop the growth of comorbidities. Attention deficit and impulsivity and Hyperactivity are the main signs of ADHD, and bioinformatics research have identified additional allelic regulatory genes as well as independent associated genes. Epidemiological According to research, the following environmental factors are linked to ADHD: maternal mental health issues, violence, stress, drinking and smoking, children's psychosocial difficulties, and the mothers' mental health throughout early life and pregnancy.

As to the National Institute of Mental Health (NIMH), impulsivity and hyperactivity will persist into adolescence and adulthood in 70% of children diagnosed with ADHD [2]. The proliferation of research endeavors targeted at comprehending the electrical patterns and connections of the brain during ADHD can be attributed to the advancements in medical technology and the application of diverse analytical instruments. Males' higher genetic susceptibility and propensity to react negatively to some early life stresses are likely contributing causes to this gender-related disparity. According to population-based research, among adolescents and kids with ADHD, the ratio of male to female sex is roughly 2.5:1, which is higher than other learning disabilities but lower than significant aggression or autism. However, the statistics show that millions of girls in the US and throughout the world can and do have ADHD. However, by age, the sex ratio narrows, showing that (a) Compared to men, women report relevant symptoms more frequently; (b) Compared to forms only characterized by impulsivity and hyperactivity, the condition's inattentive forms are more common among women, which are also more likely to remain; and/or (c) There is a greater possibility of adult-onset ADHD cases in women. Girls with ADHD may exhibit challenging developmental patterns. There is a significant risk of self-harming which can be made worse by early maltreatment and mediated by comorbidities, issues with reaction inhibition, and unhealthy peer relationships in adolescence. Other key effects include a high chance of an unplanned pregnancy and persistent issues with work and academics. Understanding relevant developmental pathways requires the use of several levels of study.

In addition, females are more likely to turn to the anger and inward within and be more verbally aggressive than boys, individuals also prefer to express their frustration and become more physically aggressive. This puts girls at risk for eating disorders, anxiety disorders, and depression. Compared to females (6%), males (13%) are diagnosed with ADHD more frequently than girls. The diagnosis of ADHD is more common in non-Hispanic Black and White children (12% and 10%, respectively) than in Hispanic (8%) or Asian (3%). Studies on family histories have also revealed a significant connection between drug abuse and the start of ADHD.

There are various steps involved in establishing whether a child has ADHD. The diagnosis of ADHD cannot be made with a single test. To diagnose ADHD, parents, teachers, and even the child themselves offer a history of the condition along with a checklist for rating the symptoms. Figure 1 represents the normal brain and ADHD brain and its symptoms.

Figure 1(b) shows regions of brain functional connectivity shown by yellow glowing areas; compared to normal brains, there are less neural connections between the prefrontal cortex and individuals with ADHD. There are three main categories for symptoms: Impulsivity, hyperactivity, and inattention. Below Figure 2 shows the different types of approaches to detect ADHD.

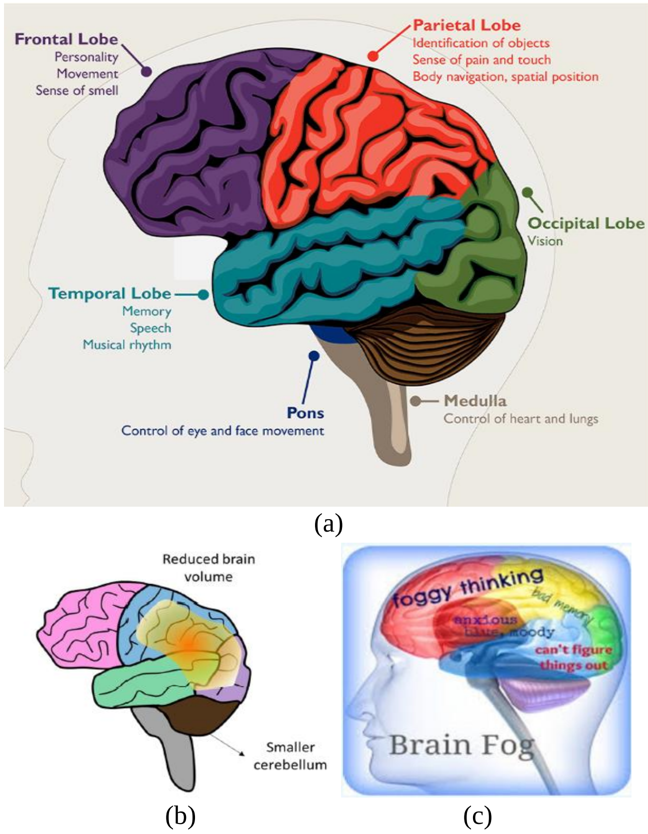


Figure 1. (a) Schematic drawing of normal brain; (b) ADHD brain; (c) Symptoms of ADHD [3]

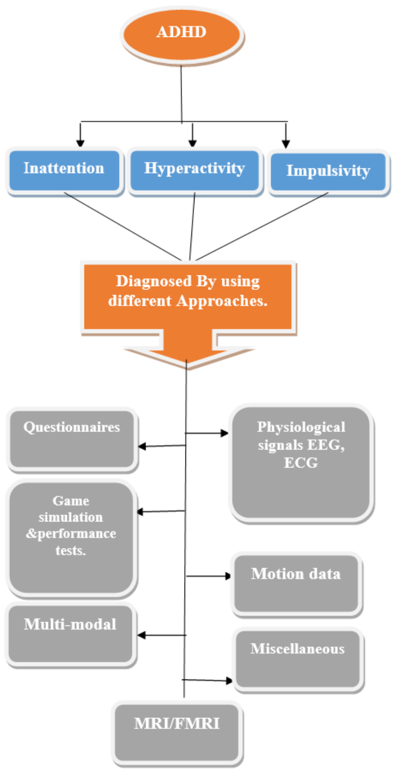


Figure 2. ADHD types and diagnosis techniques

• Inattention:

1) forgetfulness in routine duties or work.

2) Performing duties or work with careless mistakes.

3) Having difficulty maintaining focus on tasks.

4) Cannot finish tasks.

5) Is unresponsive when addressed directly.

6) Reluctance to take part in activities requiring sustained concentration.

7) Loses things easily that are needed for duties.

8) Easily distracted away from external stimuli.

9) Frequently forgetful when doing everyday duties.

• **Hyperactivity:**

1) Someone who is always on the move, especially in unsuitable settings like cinemas.

2) excessive hand fidgeting.

3) Tapping their feet on the ground or using their fingers to tap surfaces.

4) Talking too much.

5) Having trouble relaxing and having quiet time.

6) Constantly moving.

• **Impulsivity:**

1) Stopping someone off in discussion or answering before the question has been fully addressed.

2) Planning without taking the long-term consequences into consideration.

3) A difficulty in maintaining self-control

The well-established negative effects of untreated ADHD on social functioning, career opportunities, academic achievement, and life itself raise death rates. There is a great need for treatments since the predicted yearly costs to the state and individual combined are €17,769 per person [4].

A high heritability estimates in the range of 80% has been found in several twin studies for both dizygotic and monozygotic twins.

Researchers are looking at the number of youngsters with ADHD to reduce the risk factors. An investigation revealed a strong genetic correlation between ADHD and inherited variables. In younger children, around 75% of the risk of ADHD is due to genetic factors.

The risk factors of ADHD are divided into three categories: genetic, environmental, and other. There is a strong genetic component to ADHD. A parent or sibling with ADHD increases the child's chance of developing the disorder, which frequently runs in families. The condition is linked to specific genes that regulate dopamine, like DAT1 (a dopamine transporter gene) and DRD4 (The dopamine D4 receptor gene), which alter neurotransmitter activity. Research indicates that 70–80% of cases of ADHD are thought to be genetically based, emphasizing the disorder's substantial heritability. Among the environmental elements affecting ADHD are: Maternal smoking, drinking, exposure to toxins (like lead), preterm birth, and pregnancy complications (like preeclampsia) are prenatal risk factors. Continuous pollution exposure, diet (including sugar and food additives), and parenting practices (inconsistent discipline and family conflict) are postnatal risk factors for ADHD.

ADHD may also develop more quickly or become more severe due to other factors like brain damage and psychosocial pressures [5].

In addition to conducting interviews, mental health professionals and doctors would use these diagnostic tools to determine whether a categorization system, such as the Diagnostic and statistical manual of mental illnesses, fifth edition (DSM-5), fits the diagnostic criteria for the children. Therefore, it is difficult to diagnose ADHD and CD early because of the time-consuming, costly, symptom behaviours are typically well-established before the diagnostic process takes place, The diagnostic process for ADHD entails a number of phases including the collection of comprehensive data from the kid, parents, and teachers, among other sources. A vital resource for clinicians is the DSM-5, or Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition. The diagnosis is predicated on particular criteria that fall into two categories, according to the DSM-5: inattention and hyperactivity/impulsivity. Symptoms of inattention include inability to focus on work for extended periods of time, thoughtless mistakes frequently made, difficulties planning activities, and distractions or forgetfulness in day-to-day activities. Fidgeting, being unable to sit still, talking too much, having trouble waiting their time, and interrupting others are symptoms of hyperactivity and impulsivity. These habits need to be widespread, which means they need to happen in a variety of contexts (such the family and the classroom) and seriously impede the child's ability to operate in social, intellectual, or professional domains. This comprehensive approach guarantees a thorough comprehension of the child's behavior and aids in distinguishing ADHD from other possible causes [6, 7]. Furthermore, since rating scales and interviews might introduce bias, these "gold standard" diagnoses for ADHD and CD may be misdiagnosed because of their subjectivity, especially when they depend on reports from teachers, parents, or caretakers. The possibility of a misdiagnosis is further increased by the similarities between the clinical signs of CD and ADHD.

Research indicates that 4% or more of school-age children in American schools have ADHD. According to a recent survey, 5.9%–7.1% of school-age children have ADHD. According to different retrospective research, the average rate of ADHD in children worldwide ranged from 5.29% to 6.48%. According to studies, boys and children are far more likely than girls to experience ADHD. According to clinical research, males with ADHD experience functional impairments that are like those of girls with ADHD. However, one of the most significant features of ADHD is that it frequently interacts with other mental diseases; throughout the process of clinical therapy, it is essential to recognize and address these comorbidities.

The diagnosis of ADHD is still unclear among experts even in developed countries, and the disease cannot currently be reliably detected by methods such as Computerized Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI) scans. Children may be diagnosed incorrectly or with a higher likelihood of receiving a false-positive result. Incorrect medications and treatments worsen the condition in cases of misdiagnosis. Stimulants are given to children to enhance the frequency, but no parent likes giving their kid medicine they don't need. Negative effects of these medications include appetite loss, mood disorders, heart problems, and high blood pressure.

The development of high-throughput processing and high-resolution brain imaging technology has made it possible to use the quantitative characteristics taken out of the images to develop a method for computer-aided mental health diagnosis methods for imaging the brain, including magnetic resonance imaging and computed tomography, have revealed ever more perspectives and have helped identify the pathophysiology of ADHD. Because MRI can produce high-resolution images of the inside tissues, it is the perfect tool for researching brain illnesses. To examine the measurable characteristics pointing to different levels of brain changes in cortical and subcortical measurements, in recent years, diffusion properties, functional connectivity (FC), morphometric characteristics, Numerous research on ADHD have made extensive use of diffusion MRI (dMRI), structural MRI (sMRI), and functional MRI (fMRI). The basis for a neurobiological diagnostic is the physical information about the brain obtained from impartial measures, such as EEG, PET, sMRI, and fMRI, as opposed to symptomatologic diagnosis, which uses subjective rating.

Electrodes are attached to the scalp during electroencephalography (EEG a process that captures and keeps track of voltage variations and electrical signals generated by brain cell activity. EEG is a non-invasive method that tracks and assesses signals while keeping an eye on brain activity over time. Consequently, EEG analysis is done to address health issues related to brain activity. Research on brain-computer interfaces, biomedical engineering, and neuroscience are a few fields that use EEG data to gain a better understanding of an individual's cerebral activity [8]. The EEG is an essential component of data for many neuroscience investigations due to its cost-effectiveness and non-invasiveness. However, the capacity to identify the association between attributes and develop a useful automated diagnostic is limited since these results depend on hypothesis testing using small sample numbers between the experiment and control groups [9].

Different biological signals are produced by certain data techniques, which provide a comprehensive description of brain condition and helpful bio-information for the final ADHD diagnosis. Regional homogeneity (ReHo) and the amplitude of low frequency fluctuation (ALFF) are two of the most often utilized bio-signals, along with cortical thickness and grey matter probability. One of these bio-signals, FC (functional connectivity), has been demonstrated to be highly successful in distinguishing between people with ADHD and healthy controls [10].

Another non-invasive method for imaging different brain structures is structural magnetic resonance imaging, or sMRI. This technique creates sequences of contrast between brain tissue using changes in excitation rates and repetition rates. The volumetric measurements of the brain's structure are produced by these sequences. Brain diseases can be identified using machine learning models that incorporate measurable characteristics and biomarkers, as demonstrated by fMRI and sMRI, such as early circumference enlargement and brain volume overgrowth.

It is possible to think of the human brain system as a large and complex structure that manages the entire body. When comparing brain imaging data from frustrated instead of healthy individuals. EEG can be used in conjunction with functional magnetic resonance imaging, or fMRI. demonstrate the morphological and oscillatory patterns of the brain's neuronal tissue as it develops from childhood to adolescence. fMRI study has revealed several abnormalities and deviations from the brain networks of healthy individuals in the growing brain networks of individuals with ADHD.

A popular noninvasive method for assessing brain activity and demonstrating the gradual variations in Blood Oxygen Level Dependence (BOLD) throughout several brain regions during task or resting states is fMRI (functional magnetic resonance imaging). As machine learning has advanced, researchers have focused increasingly on using fMRI data to predict neuro-developmental illnesses such as ADHD, ASD, Alzheimer's disease, etc.

The subjective scoring of ADHD patients using several Hamilton scales is currently used for clinical diagnosis; symptomatologic aspects are identified by direct observation of the patients. However, it has a limited capacity to identify probable ADHD bioinformation and requires experienced clinicians. Subjectivity is introduced when doctors utilize their own discretion to determine if activities satisfy ADHD thresholds, even while using standardized criteria. Potential for Misdiagnosis: Impulsivity and inattention might be mistaken for other mental health issues, such as learning difficulties, mood disorders, and anxiety disorders. If the physician does not carefully consider other plausible explanations for the symptoms, this overlap may result in a mistaken diagnosis. Learning challenges, autism spectrum disorder (ASD), and oppositional defiant disorder (ODD) are among the conditions that frequently co-occur with ADHD [11].

To address these issues and in addition to the fact that medical applications of artificial intelligence (AI) are becoming more and more successful. As a result, further neurobiological diagnostic techniques are proposed, and DL and ML have been applied to the classification of ADHD patients in recent years. Numerous sources of massive datasets, such as behavioral observations, surveys, and even neuroimaging data, can be analyzed by computational systems. These technologies can provide more objective assessments of symptoms associated with ADHD by spotting patterns and correlations that human clinicians might overlook. Large datasets can be used to train machine learning algorithms to predict the likelihood of ADHD based on behavioral, environmental, and genetic information. Clinicians can make better decisions about diagnosis with the help of these prediction models [12].

2. RELATED WORK

Over the years, many techniques and algorithms were described for ADHD detection and classification and some of them are as follows:

Amado-Caballero et al. [13] developed cutting-edge convolutional neural networks are used to analyse 24-hour activity data and identify spectrograms of activity windows and used SVM and CNN classifier in a cascade to get a diagnosis and achieves the average sensitivity of up to 97.62%, specificity of up to 99.52%, and AUC values exceeding 99%.

This study’s primary contribution was to assess how well the following machine learning techniques performed for classifying ADHD using SPECT images: k-Nearest Neighbors(k-NN), Decision Tree, Naive Bayes, Multilayer Perceptron (MLP), and SVM (Support Vector Machine). The best results were obtained with 98% accuracy using SVM and k-NN [14].

In this research conducted by Dubreuil-Vall et al. [15], time-frequency decompositions (spectrograms) of many channels are used in electroencephalography (EEGThe 40 people in the sample consisted of 20 healthy adults (10 men and 10 women) and 20 adult ADHD sufferers (10 men and 10 women) whose EEG data was recorded during the EFT. The DL method CNNs (Convolutional neural networks) of four layers each employ filtering and pooling. This model achieves 88%±1.12% classification accuracy.

Amado-Caballero et al. [16] provided the quantitative examination of occlusion maps within gender and age subgroups. The 139 children in our set of subjects range in age from 6 to 15. DSM-V states that 70 of them have a combined ADHD diagnosis, with the remaining 69 being in good health. Particularly, occlusion maps and other CNN visualization methods are utilized, the frequency patterns of nocturnal and diurnal activity in each group revealed a substantial difference between the controls and the people with ADHD. Variations in the male population were also evident in the temporal dispersion.

Mooney et al. [17] created a competitive model for forecasting time-efficient, low-expense clinical assessments for attention-deficit hyperactivity disorder diagnosis. With the Michigan-ADHD-1000, a multi-stage Bayesian classifier produced a result with a high accuracy of (>86%).

The main goal of this research of Yeh et al. [18] was to create a virtual reality (VR) classroom that would work in tandem with an intelligence evaluation model to help doctors diagnose ADHD. In this work, visual, aural, and visual-audio hybrid distractions were generated during attention tasks in an immersive virtual reality classroom embedded with sustained and selective attention tasks. Thirteen healthy participants and 37 ADHD participants participated in a research trial. The performance of VR tasks was compared with the data from BRS, and rank-sum tests and Pearson correlation were used for analysis. The findings indicated that 23 of the 28 characteristics might be used to differentiate between children with ADHD and those without. A few task performance and neurobehavioral assessment aspects were also linked to BRS traits. With a mean accuracy of 83.2% for repeated cross-validation, our method has considerable promise for assisting medical professionals in diagnosing ADHD.

In this study presented by Chen et al. [19], the main aim is to use multiscale brain functional connectome data to build a multichannel deep neural network (mcDNN) classification model. When compared to scDNN models that used the features of the brain connectome at each individual scale and PCD independently, the mcDNN model using combined features—a fusion of the multiscale brain connectome data and PCD—achieved the best performance in the cross-validation for ADHD detection, with an AUC of 0.82 (95% confidence interval [CI]: 0.80, 0.83). The mcDNN model obtained an AUC of 0.74 (95% CI: 0.73, 0.76) in the hold-out validation.

According to the study of Zhou et al. [20], early adolescents ADHD is diagnosed with structural and functional MRIs. In this test subjects included comorbidity-free ADHD individuals as well as the healthy, children aged 9 to 10 who were covariably matched and chosen from the Adolescent Brain and Cognitive Development (ABCD) research. using Multiple Kernel Learning (MKL) and the best result obtained was 0.698 of AUC, 64.3% of classification accuracy, 0.609 sensitivity, 0.676 of specificity, 62% of F1 score.

The goal of this work of Mao et al. [21] was to develop an automated technique for diagnosing ADHD utilizing data from resting state functional magnetic resonance imaging (rs-fMRI) combined with spatiotemporal deep learning models. The author presented a method for augmenting a dataset that can split each individual subject's rs-fMRI frames into a few relatively short segments with a predetermined stride. Our technique was trained and validated using the ADHD-200 Consortium public dataset. Evaluations also revealed that our approach performed better on the dataset than conventional methods (accuracy: 71.3%, AUC: 0.80). As a result, a more precise automatic assistant diagnosis tool for ADHD can be created using our 4-D CNN approach.

Prior research on ADHD has successfully outlined the disorder's primary symptoms in a variety of age groups, set diagnostic standards, and advanced our knowledge of the genetic, environmental, and neurological risk factors. Additionally, they have assessed the efficacy of different treatments and offered insightful long-term analyses of the disorder's effects. Nevertheless, these studies frequently have drawbacks, including a lack of diversity in the sample, an emphasis on male participants, a narrow focus on symptomatology rather than wider psychosocial implications, and a preponderance of short-term research, which restricts our ability to comprehend long-term outcomes.

The latest study intends to improve research on ADHD by addressing gender disparities in ADHD presentation and treatment, as well as by incorporating a more diverse sample across regions, socioeconomic backgrounds, and ethnicities. In order to provide a more comprehensive knowledge of ADHD, it broadens the focus beyond symptoms to investigate psychosocial effects and concomitant illnesses. To evaluate long-term results, the survey might have a longitudinal component. It also makes use of current data to represent emerging patterns. Novel techniques are used, such as digital tests and multimodal data integration, which may improve theories of ADHD and provide guidance for new laws and intervention plans [22].

3. METHODOLOGY

Deep learning (DL) models are instrumental in revolutionizing disease detection and diagnosis, offering unparalleled accuracy, efficiency, and scalability in healthcare settings. They have the power to revolutionize patient care and enhance global health outcomes when included into clinical practice [23, 24].

Image processing is essential for enhancing the diagnostic capabilities of healthcare providers, facilitating the early identification, precise diagnosis, and customized treatment of illnesses in a variety of medical specializations [25].

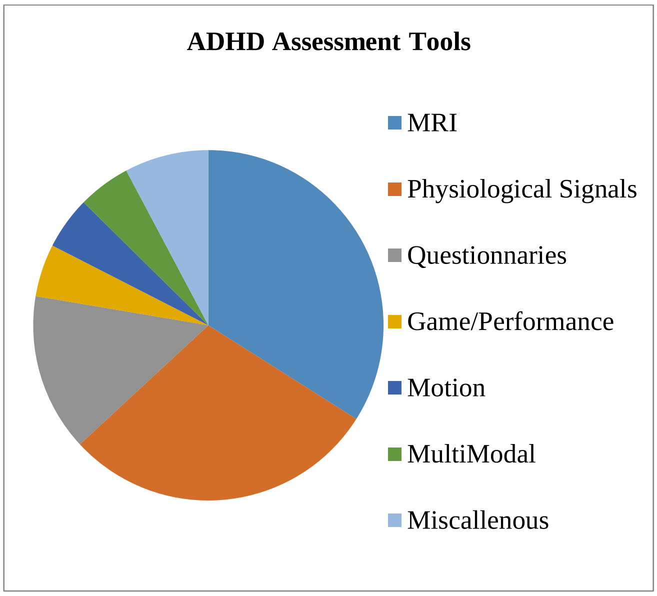


Figure 3. AI study techniques for assessing ADHD

The many types of ADHD diagnostic tests that were used in total to create AI models are displayed in Figure 3. The sections that follow with the results discuss these: Section 3.1 examines into MRI; Section 3.2 examines physiological signals; Section 3.3 scrutinizes questionnaire data; Section 3.4 investigates performance testing and game simulation; Section 3.5 examines motion data; and Section 3.6 covers all additional studies.

3.1 MRI

The scan method known as "MRI" (Magnetic resonance imaging) creates remarkably detailed images of the inside of the body by combining radio waves and strong magnetic fields. The size of the area being scanned will determine; a scan may take fifteen to ninety minutes [26]. The fact that MRI scanners are safe for the patient is their primary benefit. Their biggest disadvantage is that they can be restricted. The imaging technique that stands out for assessing brain disorders and texturing is magnetic resonance [27]. The brain's hemodynamic, biochemical, and metabolic structures can all be seen by magnetic resonance imaging. This review focuses on two of the many MRI scanner measurements: resting-state MRI (rs-MRI) and functional MRI (f-MRI).

fMRI: FMRI is widely used to assess patients undergoing epilepsy surgery. When standard diagnostic techniques are unable to help determine which parts of the brain are in charge of a certain function and where seizures first begin [28]. It has been suggested that several fMRI properties be utilized to automatically diagnose neurological and psychiatric conditions, including ADHD [29, 30]. Voxel-level features and region-level features are the two categories into which these features can be separated. AD and ADHD may be automatically detected in brain diseases by using functional connectivity (FC) networks with resting-state functional magnetic resonance imaging (rs-fMRI). Various techniques for thresholding have been developed to produce compact representations of FC networks for investigation. These studies, however, usually ignore the diversity of temporal correlation (strong connections, for example) between brain areas in subject groups and instead utilize a predetermined threshold or connection percentage to threshold entire FC networks.

A non-invasive technique with excellent spatial and temporal resolution, resting-state functional magnetic resonance imaging (rsfMRI), is being used to study abnormal brain activity in an increasing variety of neuropsychiatric diseases. The diagnosis of ADHD as a neuro developmental condition is growing. Automatic diagnostics based on neuroimaging may help medical professionals identify patients more accurately. Recent research has focused on aberrant brain functioning in ADHD using a non-invasive method to study the functional architecture of the brain called resting-state functional magnetic resonance imaging (rs-fMRI). Table 1 represents an overview of AI research employing MRI data to build a model with ML/DL.

3.2 Physiological signals

An important resource of information for illness diagnosis, treatment, and rehabilitation is physiological signals. The characteristics associated with the physiological function of several systems, including the respiratory, neurological, and circulatory systems, are represented by these signals [31].

ECG: According to some research, neurological and behavioural illnesses like ADHD and CD (conduct disorder) demonstrate changes in the autonomic nervous system-mediated brain-heart connection [32]. Therefore, it has been shown that when performing in activities like aerobic exercise or viewing film clips, people with ADHD, CD, and people with ADHD who also had CD (ADHD+CD) exhibited faster heart rates. The early repolarization abnormalities in children and adolescents with ADHD are strongly correlated with the features of the ECG. Based on ECG characteristics, AI techniques such as deep learning (DL) and machine learning (ML) can be used to assess the patients' ECG results and categorize them into groups that correspond to disorders like CD or ADHD.

EEG: Diagnosing ADHD in youngsters is most effectively done when to do a complete neurological examination and have medical professionals carefully note and monitor any symptoms. When performing medical examinations on youngsters, EEG tests are frequently necessary [33]. Electrodes are positioned on the patient's skull to pick up the weak electrical signals produced by brain neurons, and a specialized equipment records them. One of the most important uses of ADHD is the identification and treatment of the disorder since ADHD can result in abnormal EEG curves [34]. Medical staff members have a difficult time analyzing EEG data alone since the diagnosis of ADHD and analysis of EEG data are primarily the responsibility of licensed physicians. They also frequently must interact with a lot of complicated data to perform monitoring. Each child's EEG data has an accuracy range of ten hours to several days. Depending only on manpower analysis has extremely low efficiency and takes a lot of time. Rich information on the functional dynamics of the brain is coupled with electroencephalogram (EEG) data. Table 2 represents an overview of AI studies that used MRI data to create a model with EEG and ML/DL.

3.3 Questionnaires/rating scales

Medical experts diagnose ADHD using a few questionnaires and rating scales [35]. There are just six research in this area that examined data from questionnaires and only machine learning models and evaluation scales were recommended. Machine learning classifiers, including Random Forest and Support Vector Machine classifiers, Logistic Regression, Decision Trees, etc. are frequently suggested for the analysis of questionnaire data. We will only discuss the questions that have been used by research to create their most effective models.

Conner's' Rating Scales: CRS are frequently used to evaluate that ADHD affects a person's social interactions, such as the way they behave at work or in school. Parents fill out the parent rating scales (CPRS), Conner's Adult ADHD Rating Scales (CAARS), conversely, rely on self-reported information [36].

"DIVA" Diagnostic Interview for ADHD in adults: The Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV) provides the fundamental criteria for diagnosing ADHD in the semi-structured DIVA interview. In five domains of daily life—social interaction, hobbies, relationships, work, and education—interviews are utilized to assess the presence of ADHD symptoms [37].

"BRIEF-P" (Behavior Rating Inventory of Executive Function – Preschool version): contains 63 items that teachers or parents can use to assess a child's executive functioning. These items cover working memory, planning skills, emotional regulation, and organization. Their machine learning models were developed using this questionnaire [38].

ASRS (Adult ADHD Self-Report Scale): The WHO developed ASRS, which, according to DSM-IV criteria, is divided into eighteen components. People assess their own symptoms using the ADHD Negative Symptom Checklist (ASRS) [39].

"MMPI-2" (Minnesota Multiphasic Personality Inventory-2): The only required responses on the 567-item MMPI-2 questionnaire are "true" or "false." As part of ASRS's ML model development process, MMPI-2 is also utilized. It is frequently utilized to assess several mental health conditions other than ADHD, including anxiety, psychopathy, and depression [40].

"SRS" (Social Responsiveness Scale): It measures social skills in people between the ages of 4 and 18 using a 65-item examination. This survey was designed to help distinguish between people who have autism spectrum disorder (ASD) and those who have ADHD [41]. Table 3 represents an overview of AI studies using input from questionnaires.

3.4 Game simulation and performance tests

It is discussed how to diagnose ADHD using traditional performance exams and gaming simulations. in this particular section. To train their algorithm to identify ADHD, the researchers utilize performance assessments and gaming simulations, respectively [42-44]. Neuropsychological tests that evaluate a person' s ability to pay attention for extended periods of time are the Reverse Stroop task (RST) and Continuous Performance Test (CPT). To pass the computerized CPT test, candidates must accurately respond to a predetermined stimulus.

The main objective of game simulations is to provide an interactive environment that can be customized to the user's preferences [18]. A virtual reality (VR) classroom was developed by Berger et al. [45] and included a few assessments, including the CPT, for the diagnosis of ADHD. Additionally, they programmed specific " distractions " into their virtual reality system, like "thunder shower &quot, " door open " and " teacher standing up" .and after that, they gathered the user's fast response time, and test results. Different game-based ADHD detection techniques [42-44, 46], are presented and among them. Yeh et al. [18] has better accuracy and Song et al. [42] have better AUC. In performance mode, Slobodin et al. [46] had better results compared to other performance mode techniques. Table 4 shows a summary of AI research based on gaming simulations and regular performance testing.

3.5 Motion data (Accelerometer actigraphy)

Another diagnostic sign for ADHD is motion activity. There are two forms of motion activity measures: accelerometer and actigraphy [47]. Usually, an accelerometer is worn on the dominant leg' s wrist and ankle, it records both actigraphy and accelerometer data. Studies that looked at the two kinds of motion data were primarily split based on the subjects' degree of activity.; Accelerometers measure motion during routine daily activities, while actigraphy examines the subject' s efficiency during sleep. As a result, some studies have discovered that ADHD patients walked more while they slept than the control group. and this is linked to increased sleepiness during the day. This indicates that a well-known characteristic of ADHD is increased activity level, this can be easily monitored using wrist-worn accelerometer sensors and can be observed in their everyday activities. Either way, the accelerometer that records the motion data is made in a way that is not noticeable to the participants, so they are free to act naturally in the environment. With EEG or polysomnography recording techniques, this would not be possible because the participants are not familiar with the laboratory where data collection takes place. It may also be quite difficult for them to have to attach a lot of electrodes. This might thus influence the quality of the information gathered. Table 5 shows the summary of AI studies using input from Motion data.

3.6 Miscellaneous (Twitter, pupillometric, genetic, and MEG)

The least popular methods of diagnosing ADHD that ML studies have used are discussed in this section.

As social media has grown, Twitter has developed into a possible tool for identifying ADHD in the users it attracts [48]. In the absence of professional support, most mentally ill people eventually develop suicidal ideas because they are unable to ask for support from mental health care professionals. As a result, on social media, these people feel at ease discussing their mental health problems in an open manner like Twitter while looking for community members to connect with and support. As a result, social media platforms may be used to stop suicide thoughts and behavior's and diagnose mental diseases early. While just one researcher had examined Twitter data, four authors had used pupillometric data. It' s interesting to note that studies on ADHD patients show anomalies in the norepinephrine system of the brain, which is connected to the dynamics of pupil size. In 2017, studies that tracked the pupils' sizes in children with ADHD discovered that when these kids concentrated on memory-related tasks, their pupils grew bigger. Those with ADHD may be able to be diagnosed by their uncontrollably moving eyes, as demonstrated by the research on machine learning carried out by Das and Khanna [49] and Varela Casal et al. [50], Guntuku et al. [51] has obtained better specificity, sensitivity using ML and K-fold Cross validation techniques.

Loh et al. [3] and Guntuku et al. [51] used twitter data for ADHD disease and achieved a better AUC of 0.836. The SVM classifier is used in both pupillometric and twitter modes and obtained more than 95% accuracy using 30-fold CV and 0.836 AUC using fivefold CV. The risk that someone may be diagnosed with ADHD is believed to be affected by genetics. There is strong evidence that certain genes in the serotonergic and dopaminergic systems—such as DBH, SLC6A3 (DAT1), and DRD4—are associated with a higher risk of attention deficit hyperactivity disorder (ADHD). A meta-analysis of genome-wide association study has shown 27 human genes linked to an increased risk of ADHD. This figure is over twice as high as what was discovered in earlier research. Research indicates that there is a higher likelihood of Attention Deficit/Hyperactivity illness in children born to individuals with the illness. It seems unlikely that a single genetic error is the cause of ADHD, and the inheritance pattern is most likely complex. Table 6 shows a summary of AI research based on miscellaneous.

3.7 Multimodal

A high heritability estimates in the range of 80% has been found in several twin studies for both dizygotic and monozygotic twins [52-55]. Therefore, because the usual methodology was not followed by the genetic indicators for finding genetic variants linked to risk in genome wide association studies (GWAS).

The above are the number ways to detect ADHD based on the previous study.

Through deep learning, a computer model gains the ability to classify objects based only on their photos, texts, or sounds. Modern accuracy levels can be attained by deep learning models, sometimes even surpassing human performance. Large amounts of labelled data and multi-layered neural network designs are used to train models. When utilizing fMRI (functional magnetic resonance imaging) scans to detect ADHD (attention deficit hyperactivity disorder), deep learning is an essential component of image processing. This is related: Figure 4 below depicts the deep learning procedural model.

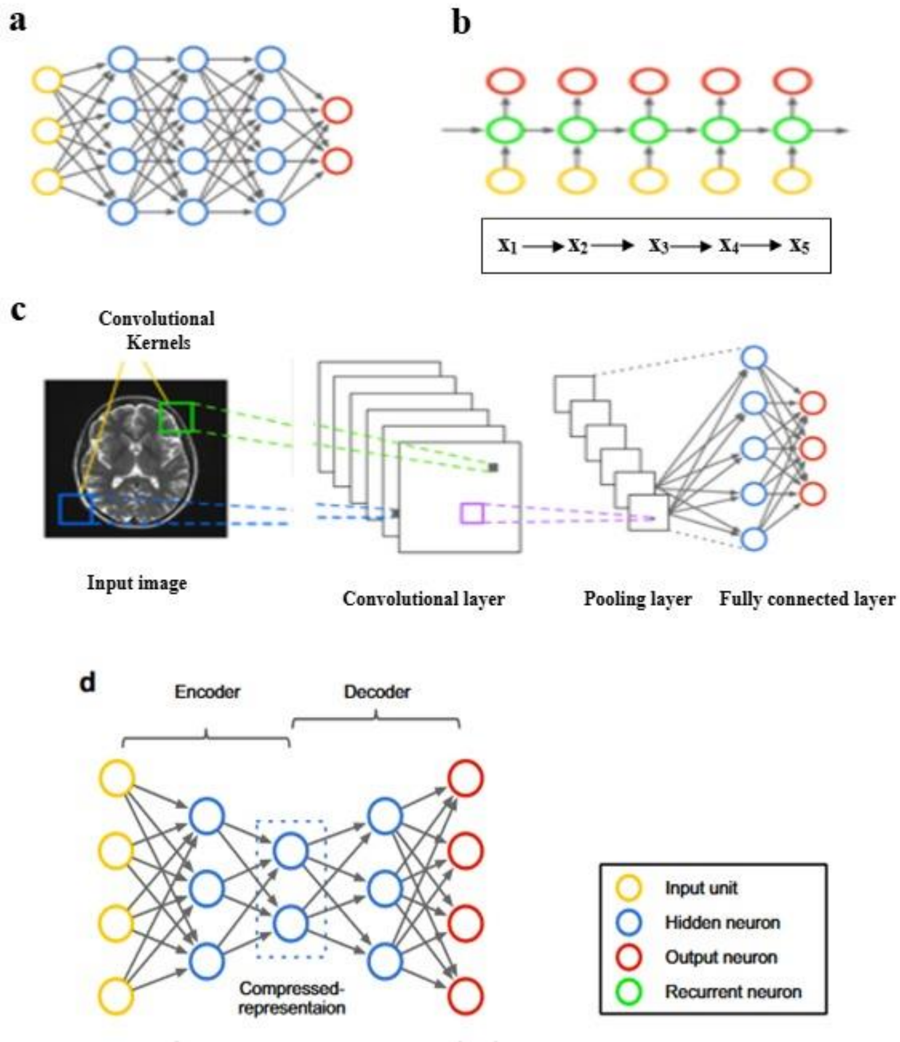


Figure 4. Deep learning procedural model [56]

Computational approaches to ADHD diagnosis have the potential to revolutionize clinical practice and yield major advantages for patients and physicians alike. Through increased diagnostic precision, streamlined procedures, and customized care, these instruments can enhance patient results and increase healthcare accessibility. But in order for integration to be successful, issues with adoption, ethics, training, and regulations must be resolved. By carefully addressing these issues, the field can better diagnose and treat ADHD patients by utilizing computational methods, which will ultimately improve care for those with the illness [57].

The McCulloch-Pitts model of a neuron explains how a neuron receives inputs and produces outputs. The fundamental formula for the McCulloch-Pitts neuron model is as follows:

$$y = \begin{cases} 1 & \text{if} \sum_i xiwi \geq \theta \\ 0 & otherwise \end{cases} \tag{1}$$

where, y represents the neuron's output, which might be 1 or 0; wi is the weight that has been allocated to the i-th input. The input value for the i-th input channel is denoted by xi. The sum $\sum_i xiwi$ reflects the inputs' weighted sum; the threshold is a predefined value that determines when neuron fires.

In a neural network, activation functions are mathematical operations performed on a neuron's output. They give the network non-linearity, which enables it to discover intricate patterns and connections in the data. There are numerous activation functions available, and the type of problem being solved will determine which optimization function is best. Frequently employed activation function is Softmax Function (for classification of several classes):

$$softmax\ of(x_i) = \frac{ez_i}{\sum_j e^{xj}} \tag{2}$$

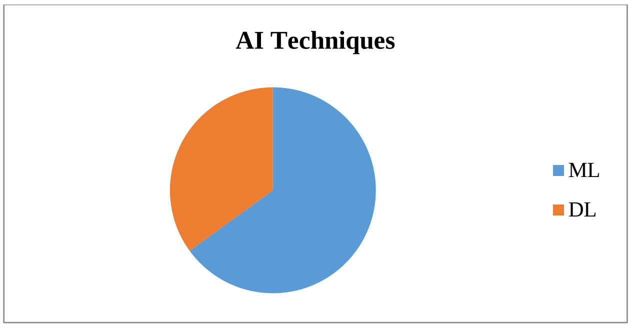
The following are some frequently used activation functions and their corresponding equations: Optimization functions, sometimes referred to as loss functions or cost functions, calculate the difference between a model's expected output and the desired output that is achieved. Reducing this disparity will help the model's prediction accuracy, which is the aim of optimization. There are numerous optimization functions accessible; the one to use will depend on the kind of output the model produces and the nature of the problem that must be solved.

commonly used optimization functions in deep learning and machine learning are:

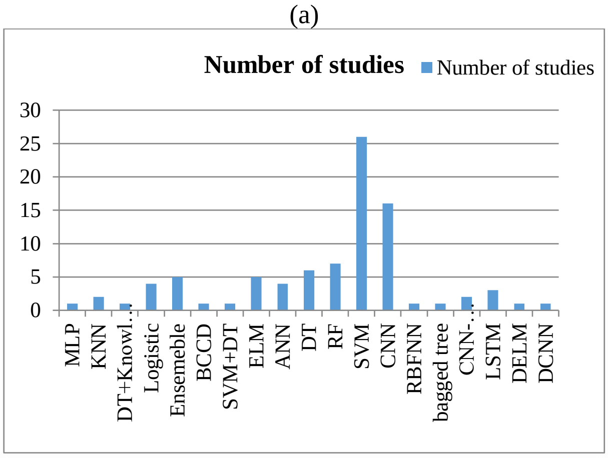
$$y = f(\sum_{i=1}^{n}(xiwi - b)) \quad (3)$$

where, *xi* is the neuron's input data, *wi* denotes its connection weight, *b* denotes its threshold, *f* denotes its activation function, and *y* denotes its output data.

Figure 5 presents the Summary of AI techniques and number of ML and DL classifier used for ADHD diagnosis and detection. They examined a total of DL and ML investigations for ADHD diagnosis. In machine learning (ML) research, the most often used classifier is SVM, however in DL research, convolutional neural networks (CNNs) are preferred models. Keep in mind that CNN and SVM are not inherently better than other DL or ML models. An appropriately planned clinical investigation that evaluates the models in real clinical settings with direct patient interaction with ADHD patients determines if an ML or DL model is applicable.



(a)



(b)

Figure 5. (a) Summary of AI techniques and (b) number of ML and DL classifier used for ADHD diagnosis and detection

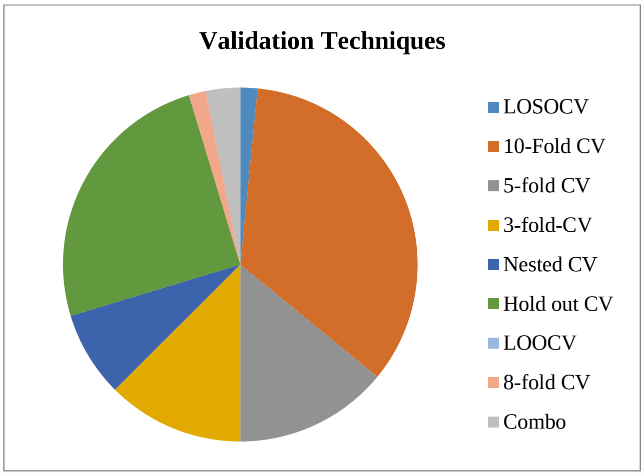


Figure 6. The validation using AI techniques for ADHD detection

The model's applicability is determined by the features and datasets that were used to train the classifier.

Figure 6 presents the different validation procedures used in the AI studies.

The most popular validation methods used in AI research to assess models are leave-one-out, hold-out, and 10-fold cross-validation. A reliable validation technique called the K-fold CV method splits datasets into k folds. Model training will be done on the remaining fold, while model evaluation will be done on one-fold. To ensure that every fold was employed for the model's training and testing, the K-fold CV iterates k times. Prediction models can be assessed using techniques like K-fold cross-validation. A fold, or subset, is created from the dataset. A new fold is used as the validation set for each iteration of training and assessment, which is done k times for the model.

The generalization performance of the model is determined by averaging performance measures over folds. A specific type of k-fold CV, with k representing the sample count of the dataset, is the LOOCV. A form of cross-validation that is like k-fold cross-validation is leave-one-out cross-validation (LOOCV), assuming k is the number of dataset occurrences. However, due to its high processing cost, it can only be applied to small datasets. The hold-out technique divides the data into two halves, one of which is used to train the model and the other for verification and testing. Its application can be advantageous for both model selection and assessment. A good way to split up big datasets into sets for training, testing, and validation is to use hold-out validation. The model is trained using the training set; it is then refined using the validation set, and its performance is evaluated using the test sets. They recommend use k-fold and LOOCV to assess the therapeutic value of the AI model since they show a significant correlation between test and training patients. Because of its accuracy, ML and DL techniques have been used in several medical applications over time. A bar chart in Figure 6 shows the quantity of published AI research on the diagnosis of ADHD for the years 2010 through 2023.

In Figure 7, a greater number of researchers using ML for ADHD, but in recent times, DL methods have been used to identify and diagnose ADHD. Before AI approach for ADHD diagnosis is taken seriously for clinical usage, there is scope for improvement. Figure 7 illustrates that although the percentage of ML studies has declined as DL research has increased, DL research was just initiated in 2017 and has not yet reached technical maturity. This is not unexpected considering the large number of machine learning research on diagnosis ADHD, making new research preferable to earlier studies has become very challenging and competitive. They have analyzed various ADHD detection and diagnosis techniques. From this analysis, we observed that most of the authors only focused on a single performance metric i.e. Accuracy. Few of them focused only on AUC. A few of them concentrated on various measures including precision, FPR, FNR, F1-score, sensitivity, accuracy, and so on. The three most important measure factors are sensitivity, AUC, and accuracy. Figure 8 shows the average accuracy, AUC, and Sensitivity.

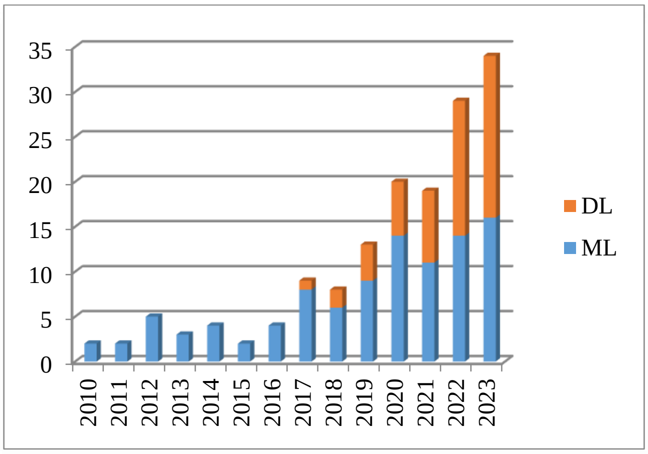


Figure 7. Quantity of AI research on diagnosing ADHD that have been published over time

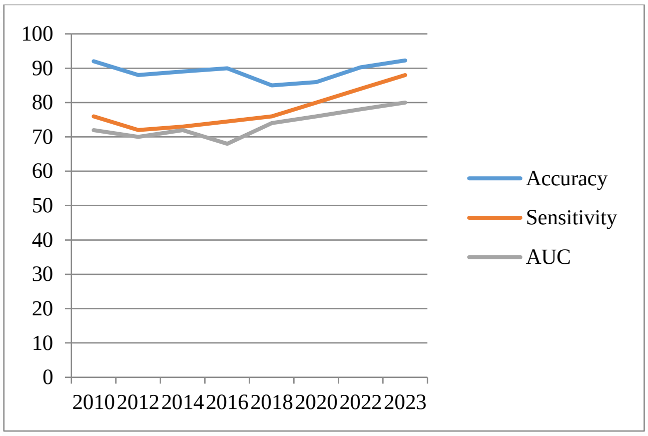


Figure 8. Performance over the years

Since 2013, across several ML and DL trials, the average model accuracy has been consistently reported between 80 and 90 percent. But as technology advances, artificial intelligence research has grown dramatically in the last few years, indicating that computer-aided ADHD identification is improving. Figure 8 represents the Accuracy, sensitivity, AUC over the years.

However, neither psychiatrists nor pediatricians presently use either diagnostic tool in normal clinical settings to identify ADHD, even though the enormous quantity of AI research that our analysis has revealed about the diagnosis of ADHD using MRI and EEG. It takes time and money to collect data from people who have been diagnosed with ADHD because both diagnostic methods can only be utilized in hospital or hospital settings. ADHD individuals may find it very difficult to remain motionless during an MRI, which increases the risk of motion artifacts that are very difficult to interpret.

One typical tool for evaluating ADHD is a questionnaire, however it might be interpreted subjectively and with bias. However, fMRI has recently demonstrated improved outcomes for the diagnosis of ADHD, Therefore, to prove its viability and carry out a clinical trial for early and precise ADHD detection and diagnosis, we want to promote more DL investigations using fMRI in ADHD diagnosis.

Machine learning-based algorithms for ADHD diagnosis are being developed and implemented by a number of clinics and universities. The first video game treatment for ADHD that has received FDA approval was developed by Akili Interactive Labs. It uses machine learning to adjust to each person's unique cognitive profile and places more of an emphasis on treatment than diagnosis. The QbTest, available from QbTech, measures symptoms of ADHD by fusing motion tracking and a Continuous Performance Test. Although it cannot detect ADHD on its own, clinicians can use machine learning to examine the data it gives to aid in the diagnostic process. Researchers at Boston Children's Hospital, the Child Mind Institute, and Cleveland Clinic have been exploring the use of machine learning for ADHD diagnosis.

Boston Children's Hospital focuses on analyzing neuroimaging data and biomarkers, while the Child Mind Institute uses brain imaging data to develop diagnostic tools for ADHD and other mental health conditions. Cleveland Clinic researchers are working on models that analyze electronic health records and neuroimaging data to improve ADHD diagnosis.

As of now, deep learning-based methods for diagnosing ADHD are mainly in the research stage and are not in general clinical use. Still, a number of top universities are creating and evaluating these models:

Stanford University School of Medicine: focuses on discovering brain patterns linked to ADHD by analyzing fMRI data using deep learning algorithms. In order to diagnose ADHD and other neurodevelopmental disorders, researchers at Harvard Medical School and Boston Children's Hospital are experimenting using deep learning models to evaluate neuroimaging data, such as fMRI.

NYU Lang one Health: To develop more precise diagnostic tools, the Child Study Center is investigating deep learning techniques to examine brain connectivity patterns in ADHD.

The Institute for Neuroimaging and Informatics at the University of Southern California (USC) has developed deep learning models to assess extensive neuroimaging datasets, potentially facilitating the diagnosis of ADHD.

Table 1. An overview of AI research employing MRI data to build a model with ML/DL

Model	Accuracy	Sensitivity	Specificity	Cross-Validation (CV)	AUC
Zhao et al. [58]	97%	73%	83%	–	–
Khullar et al. [59]	–	90%	72%	–	–
Lohani and Rana [60]	92.6%	–	–	5-fold CV	–
Liu et al. [61]	–	–	–	–	0.85

Table 2. An overview of AI studies that used MRI data to create a model with EEG and ML/DL

Model	Accuracy	Sensitivity	Specificity	Cross-Validation (CV)	AUC
TaghiBeyglou et. al. [62]	95.8%	–	–	5-fold CV	0.91
Tosun [63]	92.2%	–	–	Training 80 Test 20	–
Catherine Joy et al. [64]	96.52%	98.2%	98.82%	–	–
Ahmadi et al. [65]	95.46%	–	–	IntersubjectCV	–

Table 3. An overview of AI studies using input from questionnaires

Model	Accuracy	Sensitivity	Specificity	Cross-Validation (CV)	AUC
Morris et al. [66]	97%	73%	83%	–	–
Olofsdotter et al. [67]	–	90%	72%	–	–
Öztekin et al. [68]	92.6%	–	–	5-fold CV	–
Guttentag et al. [69]	–	–	–	–	0.85

Table 4. An overview of AI studies using input from gaming simulations and regular performance testing

Model	Accuracy	Sensitivity	Specificity	Cross-Validation (CV)	AUC
Heller et al. [70]	78%	–	–	3-fold CV	–
Yeh et al. [18]	83.2%	–	–	5-fold CV	–
Merzon et al. [71]	–	–	–	10-fold CV	0.92
Slobodin et al. [46]	87%	89%	84%	100-foldCV	0.85

Note: Neuropsychological tests that evaluate a person's ability to pay attention for extended periods of time are the Reverse Stroop task (RST) and The CPT stands for Continuous Performance Test. To pass the computerized CPT exam, applicants need to correctly answer a given stimulus.

Table 5. An overview of AI studies using input from Motion data (accelerometer actigraphy)

Model	Accuracy	Sensitivity	Specificity	Cross-Validation (CV)	AUC
Lindhiem et al. [72]	89%	93%	86%	LOOCV	–
Jaiswal et al. [73]	96%	–	–	–	–
Muñoz-Organero et al. [74]	90%	-	90%	LOOCV	–
Faedda et al. [75]	83.1%	64.4 ± 13.6%	91.7 ± 5.3%	4-fold CV	–

Note: Accelerometers measure motion during routine daily activities, while actigraphy examines the subject's efficiency during sleep. As a result, some studies have discovered that ADHD patients walked more while they slept than the control group.

Table 6. An overview of AI studies using input from miscellaneous (Twitter, pupillometric, genetic, and MEG)

Model	Accuracy	Sensitivity	Specificity	Cross-Validation (CV)	AUC
Vimalajeewa et. al. [76]	84.3%	97%	76%	–	–
Das and Khanna [49]	–	77.3%	75.3%	10-fold CV	–
Varela Casal et al. [50]	96.3%	-,	–	LOOCV	0.99
Mohd et al. [77]	82%	-	-	10-fold CV	–

Note: As a result, social media platforms may be used to stop suicide thoughts and behavior's and diagnose mental diseases early.

Table 7. An overview of AI studies using fMRI data

Model	Accuracy	Sensitivity	Specificity	Cross-Validation (CV)	AUC
Salah et al. [78]	98%	–	–	–	–
Deshpande et al. [79]	90%	–	–	LOOCV	–
Riaz et al. [80]	86.7%	77.2%	90.1%	LOOCV	–
Meng et al. [81]	82%	–	–	–	–

MIT's Computer Science and Artificial Intelligence Laboratory (CSAIL): Researchers at MIT have improved the diagnosis of ADHD and other mental health issues by creating deep learning algorithms to examine behavioral and neurological data. Researchers at the Computer Science and Artificial Intelligence Laboratory (CSAIL) at MIT have developed deep learning algorithms to analyze behavioral and neurological data, which has improved the diagnosis of ADHD and other mental health conditions. Table 7 shows an overview of AI studies using fMRI data.

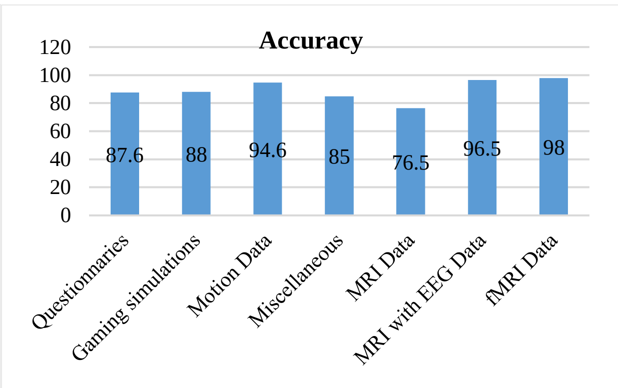


Figure 9. Performance comparison of different approaches on their ability to attain the utmost accuracy within each approach

4. COMPARATIVE STUDY

Figure 9 shows the performance comparison of different approaches on their ability to attain the utmost accuracy within each approach.

5. DISCUSSION

The "gold standard" for diagnosing ADHD often consists of a mix of behavioral observations, exams, rating scales, cognitive testing, and assessments of the efficacy of treatment plans. This takes time and is constrained by the lack of qualified diagnosticians in the world. We examined the efficacy of applying DL and ML approaches to several traditional diagnostic models, as well as sophisticated tools for diagnosis like MRIs and EEGs, such as rating scales and questionnaires. The application of computational methods to the diagnosis of ADHD presents a number of ethical challenges that need to be carefully managed in order to maximize its potential for accuracy and objectivity. Concerns regarding privacy, informed consent, and algorithmic bias are especially important because of the sensitive nature of the data involved and the possibility that these systems may have an impact on vulnerable populations. By proactively addressing these ethical issues, the field can develop computational tools that not only improve the diagnosis of ADHD but also do so in a way that is transparent, equitable, and respectful of patients' rights. This will guarantee that technological advancements will enhance the diagnosis and treatment of ADHD, ultimately improving the lives of all those affected by this condition. The results of using DL and ML techniques to fMRI. However, because ADHD has a varied clinical character, a multimodal approach may be more appropriate for this condition than the single modality method used in the single tests.

The majority of the research included in the study are well-known in the area or have been published in reputable publications. This aim may generate selection bias while guaranteeing the inclusion of high-quality studies. Studies that are less well-known may be underrepresented, especially those that come from underresourced research regions or are published in less prestigious publications. This could result in an inaccurate representation of the state of ADHD diagnosis and computational techniques at the moment. A large number of the examined research use data mostly from Western nations, including the US and Europe. This geographic focus could obscure significant variations in ADHD diagnosis and treatment approaches across different regions of the world. Consequently, the results of the survey may not accurately reflect the worldwide variety of ADHD presentations and the relevance of computational.

Summary:

In simple terms, this review's relevance is as follows: The 80 items they gathered for this review have been categorized based on the modality or dataset that was used to train their model for the diagnosis of ADHD: MRIs, mobility data, gaming simulations, physiological signals, surveys, performance evaluations, and other types of data (Twitter, Phallometric, and genetic data. When diagnosing ADHD, fMRI, MRI, and EEG signals are the modalities most frequently used in the ML and DL models. They have identified the functional connectivity properties and power spectral properties that are most frequently used for the diagnosis of ADHD in MRI, fMRI, rs-fMRI, and EEG, respectively. For research that uses rating scale/questionnaire data, to support AI models in achieving efficient diagnosis performance, the typical survey questions for ADHD have been added. A wide range of validation techniques were also uncovered in the ML and DL research, with hold-out validation and 10-fold CV being the most widely utilized validation strategies. Additionally, we have looked at the trend of research being conducted throughout time to diagnose ADHD, with a focus on the DL models that have grown in popularity recently.

Research Gaps: we Identified the gaps from the existing studies are as follows:

·One potential obstacle to the effective generalization of deep learning models for diagnosing ADHD is the scarcity of labelled datasets.

·GAN-driven data augmentation for unbalanced datasets within the fMRI framework.

·Examine how MRI pictures can be used to diagnose neuropsychiatric disorders.

·To investigate how connections between various ICNs (channels) affect the classification of brain networks to detect ADHD.

·To investigate the efficient use of clinical phenotypic data in the evaluation of diagnosis outcomes for brain diseases.

·To minimize the influence of data diversity on classification outcomes, which aims to mitigate the absence of utilizing fMRI data as a time series, which inadvertently overlooks time as an independent factor.

·To examine the parameter configurations of the pipeline and explore the integration of non-imaging data and various types of features like ReHo (regional homogeneity) and ALFF (amplitude of low-frequency fluctuation) to enhance the classification performance.

Future Scope:

The early and focused treatment of ADHD will be made possible by the proper diagnosis of the condition. Determining the precise altered functional connectivity caused by a certain illness is thought to be a crucial performance that might reveal the disorder's underlying mechanism. fMRI is a potentially useful neuroimaging method for examining the functional activity of various brain areas. Classifying neurological disorders of the brain, deep learning and fMRI imaging have advanced significantly in recent years. From this survey we observed that still there is a lot of scope for achieving more than 95% for various performance metrics like F1-score, Sensitivity, AUC, Specificity, and 100% accuracy at a time for early and accurate ADHD detection. From the survey, it is observed that fMRI has shown better results. They suggest that future research should concentrate on developing AI models that use fMRI data to track and diagnose ADHD and on expanding the quantity of publicly available datasets for the various modalities used in ADHD classification.

Therefore, to detect and diagnose ADHD more effectively and accurately. We will create a hybrid deep learning method using ADHD-200 Dataset Images Which is publicly available at https://fcon_1000.projects.nitrc.org/indi/adhd200/index.html.

Figure 10 shows the proposed architecture of ADHD Detection.

By creating modified versions of preexisting data, data augmentation [82] creates an artificial expansion of the training dataset. This can be done by using deep learning techniques to generate more data instances or by making minor changes to the original dataset. Among various augmentation techniques such as flipping, cropping, rotation, translation, color manipulation, cutout augmentation, affine transformation, Gaussian Noise, Mix-up, Sliding Window, fusion + sliding window, MCGAN, SDAM (sparse data augmentation model) based on Encoder Forest, NW, and SMOTE, fusion + sliding window has demonstrated the highest accuracy achieved i.e., 79.46%.

Feature selection [83] is the procedure of automatically or manually choosing the most suitable and pertinent subset of features to be utilized in model construction. It involves incorporating essential features or eliminating unnecessary ones from the dataset without altering them. Previous research has utilized various types of feature selection methods such as CNN, GAT, LSTM, fusion, GA-Based Feature Selection, Gini index, among others, to identify relevant features for model development. Certain approaches leverage phenotypic features, hybrid features, while others utilize image features to incorporate the necessary attributes for problem-solving.

In the realm of classification, the model undergoes complete training with the training data, following which it undergoes evaluation using test data, before being applied to make predictions on new, unseen data [84, 85]. Previous research has explored various classifiers including pooling techniques, MGF, EM-MI, 4D-CNN, RF, SVM, FCNN, BrainNetCNN, CNN-EW, hash codes, BNC-DGHL, E2N-CKEW, SSAE, AMTLCNN-EW classifiers for classification tasks. Among these, BNC-DGHL attained the highest accuracy of 69.09%.

An optimizer refers to a function or algorithm responsible for adjusting the neural network's weights and learning rate, among other parameters. Its primary purpose is to minimize the overall loss and enhance accuracy. Various optimization methods are employed to enhance model performance, including Gradient Descent (GD), Stochastic Gradient Descent (GSD), Mini-batch Gradient Descent (MGD), Momentum, Adaptive learning Rate Methods, learning Rate Scheduling, Regularization, Hyperparameter Tuning, and Advanced Optimization Algorithms.

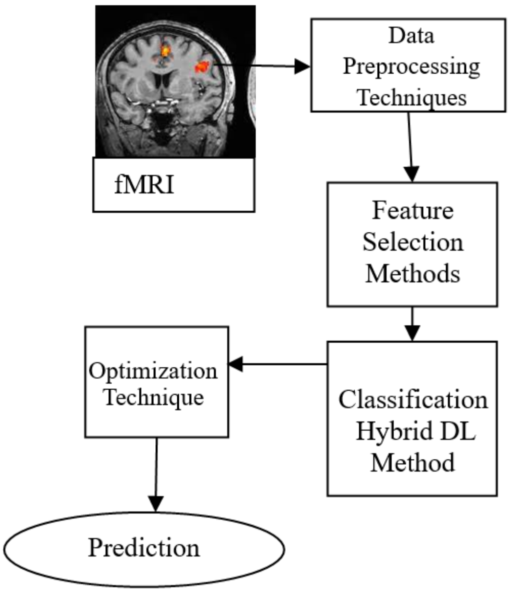


Figure 10. System architecture

6. CONCLUSIONS

This study examines techniques for the diagnosis and detection of attention deficit hyperactivity disorder. In kids and Adults, ADHD is the most common neurobehavioral condition. However, the reason for it is still unknown, which makes it difficult to develop traditional diagnostic techniques that are inexpensive, reliable, and fast. Many techniques and methods have been presented in recent times, however, still there is a research gaps for ADHD detection. Finding the limitations and gaps in the research on ADHD is the main objective of this study. In this survey, they have reviewed various research works on ADHD using Deep Learning, Machine Learning and Image processing techniques like MRI, EEG, fMRI, and rs-fMRI. Various research works and their result analysis are discussed in detail. Most of the research focused on hospital settings and used modalities like MRI and EEG; Very few research addressed other modalities. Additionally, other from MRI, for most modalities, there were very few publicly available datasets. Few researchers have used data from wearables such as accelerometers and ECGs, and none have attempted to include PPG signals.

This survey findings emphasize the significance of keeping improving and incorporating computational methods into the ADHD diagnosing process. Traditional approaches have given us a good starting point, but the developments in machine learning and expert systems have the ability to solve long-standing problems with ADHD diagnosis. The field can advance toward more precise, egalitarian, and individualized diagnostic and treatment approaches by utilizing the potential of multimodal data integration of resolving generalization and bias concerns. The potential for this advancement in ADHD diagnosis might completely change the lives of those who are affected by the disorder and guarantee that they get the best possible care all of their life. Even research also need to decrease detection time. So, that the introduced novel model will be improved in detection rate.

The symptoms and effects of ADHD are diverse and complex, varying widely from person to person. Individual differences must be taken into account for an effective diagnosis and treatment plan. Computational techniques, such as machine learning models, can improve diagnostic accuracy by sifting through big datasets and finding patterns, but they should be used in conjunction with clinical judgment rather than in place of it. Together with patients and their families, treatment plans should be created that take into account each individual's needs. Effective management of ADHD requires constant communication and frequent modifications. Future developments should combine clinical knowledge with computational techniques, and multidisciplinary cooperation is crucial to the creation and validation of novel diagnostic instruments.

Most of the researchers focused on improving the accuracy of ADHD detection. Still, there is a need to improve on several performance metrics, including F1-score, AUC, Specificity, Precision, and Sensitivity, to offer reliable and useful results for early identification of ADHD. Analysing past attempts and pointing out their shortcomings is the main objective of this work.

We will introduce a novel strategy to treating ADHD in the future, utilizing the best augmentation techniques as well as feature selection and classification techniques for the early detection of ADHD using various metrics. which, by accurately and promptly diagnosing ADHD, will address these problems and protect people's lives—especially those of youngsters.

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