Detection and Classification of ADHD Using Deep Learning Based on EEG Signals

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Abstract. Attention Deficit Hyperactivity Disorder (ADHD), a neurodevelopmental disorder, is gaining increasing public and academic attention. To illuminate the current state of ADHD research, this paper reviews a range of studies, including but not limited to epidemiology, pathological origins, patient challenges, and mainstream treatments. It also analyzes a series of experiments and studies that use automated tools to analyze physiological signals for ADHD detection and differentiation. The first section provides a comprehensive summary of existing research on the pathological origins and subtype differences of ADHD, covering multiple perspectives and levels. This lays a theoretical foundation for the idea of analyzing ADHD using EEG signals. The second section focuses on distinctions in EEG signals among individuals with normal neurodevelopment, ADHD populations, and its subtypes, demonstrating that deep learning can be used to train on such physiological signals for automated diagnosis. The third section highlights existing studies that leverage deep learning, outlining the potential developments in this field. The paper objectively analyzes and summarizes obstacles and issues that may be encountered on the research path of utilizing deep learning as a tool for automated ADHD diagnosis, offering recommendations for future development. Through this review, the progress and limitations in ADHD research become clear, providing insights for continued and more informed development in the field.

Keywords: ADHD; deep learning; EEG.

1. Introduction

Attention deficit hyperactivity disorder (ADHD) is a relatively common neurodevelopmental disorder according to DSM-5 [1], with an average prevalence of 5% among children [2]. Patients with this disorder often present with symptoms of inattention and/or hyperactivity and impulsivity in childhood or adolescence, which can persist into adulthood, and the proportion is not low, about 40% to 50%, using DSM-5 criteria [3]. The emergence of ADHD can also occur after childhood, known as late-onset ADHD. Although the persistence and stability of ADHD into adulthood has been questioned, the prevalence of DSM-5/CIDI adult ADHD is in the average of 2.8%, not much lower than that in children [4]. In terms of gender differences, the prevalence of ADHD in boys is about 2:1 to 3:1 compared to girls, with an estimated 12% in boys and an estimated 4.7% in girls. And girls were more likely to be diagnosed with inattention subtype [5].

Due to the lack of biomarkers and other objective criteria, the diagnosis of ADHD is currently a clinical diagnosis performed by a licensed clinician interviewing patients and their parents or caregivers [3]. According to DSM-5 criteria, a diagnosis requires symptoms of inattention or hyperactivity and impulsivity that are developmentally appropriate, persist for at least six months, occur in different settings, and first appear in childhood [1]. ADHD is also a diagnosis of exclusion, requiring the condition that there is no other disorder that better explains the symptoms. Some medical and psychiatric conditions can also show signs of ADHD, such as epilepsy, sleep disorder, anemia, thyroid disorders, learning disorder, and anxiety disorders, so the other historical information and physical examinations are important parts of exclusion [6]. As a comorbid disorder, ADHD often co-occurs with depression, anxiety, Oppositional Defiant Disorder, mood disorder, tic disorder, autism spectrum disorder, Conduct Disorder, and specific learning disorder such as dyslexia [7].

Due to their neurological traits, the lives of people with ADHD often encounter great challenges, difficulties, and risks, seriously affecting their family life, academic performance, social relationships, and emotional communication [2]. A meta-analysis of seven studies concluded that ADHD in children and adolescents moderately affects health-related quality of life in physical domains and severely impacts psychosocial domains. Another meta-analysis revealed that adults with ADHD exhibited significantly higher levels of emotional dysregulation, featuring more pronounced roles for emotional reactions, compared to normal controls. From preschoolers to adults, academic functions are substantially impaired by ADHD traits, particularly inattention deficits [8].

Considering its multifactorial etiological factors, diverse symptom expressions, and complex comorbidities, ADHD is generally recognized as a heterogeneous disorder.

From the perspective of etiology, this disorder has a strong genetic factor, with an estimated heritability of 76% [9]. A number of studies have identified genes that may contribute to ADHD, including dopamine receptor genes, dopamine transporter gene, noradrenergic receptor genes, norepinephrine transporter gene, and so on. However, the results of association studies on these candidate genes are not always consistent, and the conclusions drawn from different studies do not strengthen each other [10]. Although a strong genetic component of ADHD is supported by research findings and evidence, different genes have different effects on ADHD in magnitude and proportion, and each gene contributes less to the overall risk [11]. Environmental risk factors are also part of the pathogenesis of ADHD. For example, one study found that smoking during pregnancy and a low 1-minute postpartum Apgar score significantly increased the risk of ADHD, based on an analysis of prenatal, perinatal, postnatal, and maternal parameters [12]. Turning to the basic level of neurobiology, a number of pathological theoretical models for ADHD have been proposed in recent years, such as Cognitive and Motivational Impairment Models, Cognitive-Energetic Model, and Neurodevelopmental Model. In general, these three models can explain some symptoms of ADHD to a certain extent. In the cognitive and motivational model, the working memory pattern was more associated with inattention, while the self-regulation pattern was more associated with hyperactivity and impulsivity disorder. The CEM model explains ADHD from three levels, while a double dissociation model [10].

From the perspective of brain structure, children with ADHD have abnormalities in the function of brain circuits connecting prefrontal cortex, striatum, and cerebellum [3]. Other studies have also suggested that circuits important for selecting motor responses are defective in the brains of children with ADHD. In fact, studies have shown that in different subtypes of ADHD, there are also different features in some brain structures, which means that different brain structures may correspond to different symptoms and subtypes of ADHD. This also provides a basis for classifying ADHD subtypes by EEG signal analysis [3]. This is explained in detail in the next section.

2. Related Works

2.1. Pathological Differences in ADHD Subtypes

According to the DSM-IV criteria, ADHD is categorized into three subtypes: predominantly inattentive (ADHD-I), predominantly hyperactive-impulsive (ADHD-H), and combined presentation (ADHD-C) [1]. In ADHD-I, the primary features include distractibility and difficulty sustaining attention. ADHD-H is characterized by pronounced impulsiveness and hyperactivity, particularly evident in childhood, where individuals often display high energy levels and even destructive tendencies. ADHD-C encompasses a combination of symptoms from both ADHD-I and ADHD-H subtypes, indicating that individuals with hyperactivity also exhibit attention deficit characteristics.

The performance and disorder conditions of different subtypes of ADHD will be greatly different, and the treatment plan also needs to be adjusted. According to Dieter et al.'s meta-analysis, in the comparison between ADHD-C and ADHD-I, both exhibit noticeable social disorders, albeit with distinct causes and manifestations. ADHD-C faces peer rejection due to aggressive and highly hyperactive behaviors, whereas ADHD-I tends to be more solitary, introverted, and socially marginalized. This likely contributes to the slightly lower rejection rate for ADHD-I in trial data. Additionally, ADHD-I is more prone to comorbidity with learning disabilities [13], sharing commonalities with ADHD-C in terms of learning challenges [14].

The performance and disorder conditions vary significantly among different subtypes of ADHD, necessitating tailored treatment plans. In field trial-based studies, the prevalence of ADHD-C (55%) was notably higher than that of ADHD-I (27%). Conversely, in population-based studies, ADHD-I exhibited the highest percentage among the three subtypes [13]. This disparity may stem from the fact that hyperactivity and impulsivity tend to capture the attention of caregivers and diagnosticians more readily, while attention disorders manifest more subtly and are less observable. Recognizing a child's attention deficit and identifying it as a disorder, rather than dismissing it as mere "introversion" or mind-wandering, poses a challenge that requires both expertise and knowledge for parents and healthcare professionals. Hence, it is crucial to emphasize the need for clearer and more accurate differentiation and diagnosis of ADHD subtypes.

Due to the likelihood that issues related to hyperactivity and impulsivity will tend to alleviate with development, the diagnosis of ADHD-C becomes less stable during the growth process. In the later stages of adolescence and adulthood, hyperactivity and impulsivity cease to serve as effective clinical diagnostic criteria, while symptoms of inattention persist over a longer duration [15]. The above observations suggest that the physiological basis and associated brain functional structures of ADHD subtypes may exhibit significant differences, warranting further research to contribute to the precise diagnosis of ADHD subtypes.

However, despite evident differences in neuropsychological manifestations and clinical diagnosis among subtypes, at a more foundational level such as neuroanatomy and genetics, existing research results have not consistently revealed significant distinctions between subtypes or resolved conflicts among different study outcomes. Magnetic resonance imaging studies have shown that certain brain structures, including the corpus callosum, right frontal lobe, basal ganglia, cerebellum, and overall brain volume, are smaller in the ADHD population, particularly the cerebellum [13]. This suggests the presence of cerebellum-frontal lobe-striatum dysfunction in individuals with ADHD. However, there is scarce evidence confirming differentiation among ADHD subtypes in this regard.

When using event-related potentials and electroencephalograms (EEG) as study bases, abnormalities in the right frontal and right parietal regions have been observed in the ADHD group compared to the normal population. Studies indicate quantitative differences in these results for ADHD-I and ADHD-C subtypes, but they do not represent entirely distinct characteristics [14]. In summary, there is currently no conclusive evidence of physiological differences among ADHD subtypes. However, the significant behavioral characteristics and clear neuropsychological differences imply that research on subtype differentiation in ADHD remains important and urgently needs further investigation.

As mentioned earlier, compared to MRI and other neuroimaging information, EEG holds certain advantages and plays a significant role in distinguishing ADHD subtypes. Therefore, the following section of this paper will focus on describing the differences in EEG signals among ADHD and its subtypes. Additionally, it will explore the application of deep learning in classifying these signals, aiming to enhance the accuracy of clinical diagnosis for ADHD and its subtypes.

2.2. EEG Signals Differences

The electroencephalogram (EEG) is an effective method for detecting and analyzing brain activity and cognitive states. Different signals defined by frequency ranges in the EEG can be correlated with various human states, aiding in the analysis and diagnosis of abnormal conditions and brain function disorders. Signals are categorized based on distinct frequency ranges, including δ, θ, α, β, and γ (increasing in frequency within the range of 0.1-100Hz). EEG signals are easy to record, and numerous studies have demonstrated their effectiveness in assisting diagnosis. Therefore, many studies and experiments on ADHD differentiation use EEG as the detection method [16].

Signals in each frequency band are associated with different cognitive states of the brain. δ waves are closely related to gray matter and mainly appear during deep sleep and restorative sleep. θ waves are associated with subconscious activity and typically occur during mental haze or hypnotic states. α waves represent white matter and serve as a frequency bridge between consciousness (β) and subconsciousness (θ). They usually occur in a relaxed resting state, inducing the production of serotonin, promoting relaxation, and relieving pain. β waves are the most common high-frequency waves during wakefulness and play a significant role in conscious states such as memory and learning. γ waves are a relatively new discovery in the field of neuroscience, and understanding of their functions and cognition is continually evolving. Current research suggests their importance in learning, memory processing, and overall cognitive functions [17].

The etiology of ADHD is a subject of debate in the scientific community: is it caused by delayed neurodevelopment, or is it a result of developmental deviations in the central nervous system? If the former is true, it suggests that ADHD may gradually recover during development. However, the substantial number of adults with ADHD reminds us that the latter possibility is not negligible. To verify the answer to this question, EEG signal analysis can provide assistance.

If the root cause of ADHD is delayed neurodevelopment, the average frequency and ratio coefficient results of various frequency bands in the ADHD group should be lower than those in the control group, corresponding to the signal characteristics of younger healthy children. Conversely, it suggests that ADHD is likely caused by developmental deviations in the central nervous system. In a study by Clarke et al. in 2001 [18], they conducted detailed experiments, research, and repeated comparisons of EEG signal differences among ADHD, healthy control groups, and different subtypes. Their experiments involved sampling at a rate of 200Hz during a resting state. The results strongly supported the model that ADHD is caused by developmental deviations in the central nervous system. Studies have also found that in terms of measurement stability and reproducibility, relative power is significantly superior to absolute power [18].

2.2.1 Differences Between Patients and Controls

Research has revealed that the θ/β ratio demonstrates excellent efficacy in distinguishing between normal children and those with ADHD. In comparison to the healthy control group, the ADHD group exhibits increased θ wave activity levels, with larger absolute and relative values in the θ band, particularly in the frontal lobe region. Meanwhile, the activity of β waves in the posterior region decreases, accompanied by smaller absolute and relative values. The θ/β ratio comparison indicates higher slow wave activity levels in the EEG signals of the ADHD group.

Simultaneously, there are notable differences in the θ/α ratio between the groups. In the brains of individuals with ADHD, the situation in the α wave band is similar to that in the β wave band, with an average frequency lower than that of the control group and reduced activity. Therefore, the θ/α ratio has a similar effect to the θ/β ratio. Meanwhile, in the low-frequency range, clinical subjects show a higher average frequency in the δ wave band, along with higher δ/θ ratio coefficient values.

These findings collectively suggest an overall shift in the EEG signals of individuals with ADHD towards the θ wave band, providing robust support for the perspective of central nervous system developmental deviations [18].

2.2.2 Differences Between Patients with Subtypes

Compared to numerous studies supporting the differentiation of ADHD from normal children using EEG signals, there is a relatively limited and less robust body of research on utilizing EEG signals to classify ADHD subtypes. Nevertheless, there are consistent findings in research results, concluding that EEG signals of ADHD subtypes exhibit significant differences. As mentioned earlier, θ waves, θ/α, and θ/β ratios can effectively distinguish between ADHD and control groups. Moreover, these three indicators have been found to differ among subtypes in the frontal lobe region, indicating inherent differences in the neural models among ADHD subtypes.

Building on previous research in the field of neurodevelopmental disorders, θ wave activity serves as an electrophysiological marker for many childhood brain function disorders. According to measurement results, in the ADHD-C group, θ wave activity increases from the central to the frontal lobe region, while in the ADHD-I group, it decreases. From this, it can be inferred that the dysfunction in ADHD-C originates from impaired frontal lobe function, while ADHD-I may suffer from either central nervous system dysfunction unrelated to the frontal lobe or different types of frontal lobe dysfunction [18].

2.3. Applications of Deep Learning in ADHD

Various mathematical and computational methods have been experimented with to analyze EEG signals for the purpose of diagnosing ADHD and distinguishing between subtypes. These methods include machine learning techniques such as support vector machines (SVM), as well as deep learning approaches such as artificial neural networks (ANN) and convolutional neural networks (CNN) [19]. However, compared to machine learning, which requires manual feature extraction and selection, deep learning can automate the processing of raw data, autonomously train and extract features, making it well-suited for specialized, labor-intensive, and high-threshold physiological signal datasets like EEG [20].

Although the accompanying cost is the need for a substantial amount of training data to ensure the accuracy of the final model, deep learning, particularly its CNN branch, has achieved success and garnered significant attention across various fields in recent years. This success has been contingent on the availability of extensive annotated datasets [20].

Deep learning is composed of multiple processing layers, each layer having multiple abstract data representations. Through the backpropagation algorithm, deep learning can uncover complex and hidden structures in large datasets, discover implicit relationships between data, and optimize the internal parameters of the model. This continuous learning process enhances the accuracy of the model [20]. In the analysis of EEG data and ADHD detection, deep learning has shown promising results with significant research prospects. According to a summary of meta-analyses, models using deep learning to analyze EEG for ADHD detection have achieved high accuracy rates, consistently surpassing 80% [19].

While there is no need for feature extraction, clinical EEG signal recordings cannot be directly used as input for model training and require preprocessing to remove noise and artifacts. During the signal acquisition process, actions such as blinking by the participant can impact the EEG signals during rest. To mitigate or eliminate the influence of these unnecessary movements, independent component analysis (ICA) denoising methods are employed to remove eye-related signals. Brain-related independent components are used to identify blinking and muscle artifacts, which are then manually removed [15]. For continuous time-series data samples, any segments with values that exhibit abnormalities exceeding a defined threshold after cutting are discarded.Following a series of preprocessing steps, the EEG signals are formatted into a structure suitable for input into the chosen deep learning model architecture. This formatted data can then be fed into the model for training and optimization.

In the realm of deep learning architectures applied to ADHD detection, among existing studies, CNN is the most popular, while ANN also has a notable body of research analysis. The design of ANN originates from the idea that the human brain can achieve learning effects by observing fuzzy and complex data, and it can identify direct interactions between data with relatively good accuracy. In experiments conducted by Guney et al., where event-related potentials were used as features, ANN demonstrated high performance in ADHD detection, achieving an accuracy of 98.5%. However, in Bashiri et al.'s experiment, the sample size was inadequate, and control over other variables of the samples was lacking, making it challenging to convincingly validate the efficacy of ANN in this application [16]. In summary, the number of studies verifying ANN's application to ADHD is limited, and there is a lack of robustness and mutual validation among them.

On the other hand, research and application data for CNN in ADHD detection are more abundant and compelling in comparison. Compared to simple one-dimensional data, CNN models based on convolutional architecture can handle more complex data, avoiding the necessity for generating an extensive number of weights at every layer. While we commonly associate CNN with images, in reality, CNN can process most grid-like structured data. For instance, in Chen et al.'s study, EEG data was transformed into connectivity matrices and applied to the training of a CNN [21]. This characteristic, along with CNN's excellent accuracy, makes it highly popular in applications involving the analysis of EEG signals [16].

In the study by Ahmadi et al., they utilized resting-state EEG signals during a 5-minute eyes-open period from participants. A deep learning model was proposed by them, which can effectively learn features directly from unprocessed EEG signals to facilitate classification. CNNs are often considered as black-box decision-making processes, making it challenging for medical professionals to comprehend which feature of the EEG data is most crucial in facilitating the procedure of making determinations. However, the network proposed by Ahmadi et al. in their research can display the frequency ranges and brain regions that have the greatest impact on making decision. Figure1 shows part of the effect. Moreover, their system demonstrated high classification accuracy, utilizing the combination of β1, β2, and γ frequency bands, with accuracy and precision reaching 99.46% and 99.48%, respectively. Figure2 illustrates the results. This indicates the system's capability to distinguish between healthy individuals and those with ADHD and its subtypes [15]. Figure 2 showed the topographical map using EEG data.

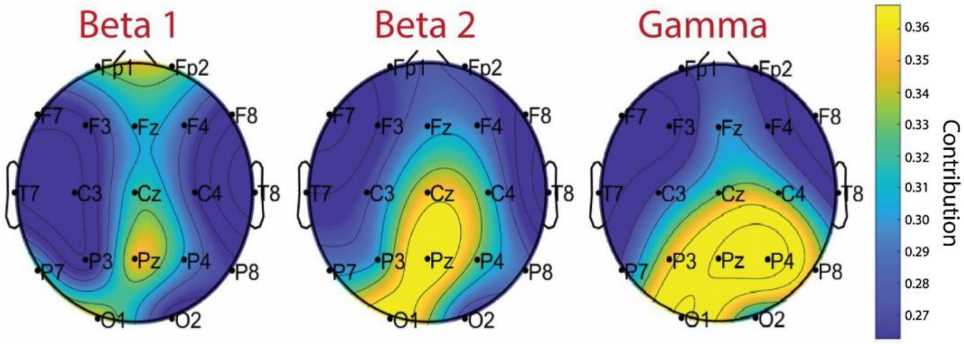

Fig. 1 Topographical map showing EEG channel contribution in classifying healthy vs. ADHD children for β1, β2, and γ bands. Warmer colors denote higher contribution [15]

In Chen et al.'s application of CNN, a novel approach to processing EEG signal data was introduced. To effectively utilize EEG signals for more efficient analysis by neural networks, they transformed EEG data into a "brain network," expressed in the form of a connectivity matrix. The brain network outlines functional connections between brain regions, leveraging knowledge from graph theory, where vertices and edges represent channels and connections between channels in EEG data, respectively. In this way, multi-channel EEG data is transformed into grid-like structured data and fed into the CNN. The framework proposed by Chen et al. achieved remarkable outcomes, with a validation accuracy of 98.17% and a test accuracy of 94.67% [21].

Vahid et al. employed the EEGNet deep learning architecture, with an input in the form of a binary tuple (C, T), where C represents the number of channels in EEG, and T represents the time points. However, the results obtained from their model training were slightly inferior to the aforementioned studies. The accuracy in distinguishing between ADHD and healthy controls was approximately 83%, while the classification accuracy for ADHD subtypes was only around 69%, insufficient for supporting the differentiation of subtype patients. This indicates that further exploration and research are needed in the application of deep learning for classifying ADHD subtypes [22].

As mentioned earlier, the diagnosis of ADHD still relies on specialized and trained healthcare professionals. On one hand, the number of highly experienced medical personnel is limited, and on the other hand, non-automated, subjective diagnostic methods are prone to errors. In such a scenario, the automation of ADHD diagnosis using deep learning becomes an anticipated and worthwhile endeavor. Furthermore, the potential demonstrated by deep learning in classifying ADHD subtypes holds the promise of assisting clinicians in achieving more precise diagnoses, thereby improving treatment plans tailored to different subtype patients. Simultaneously, the use of EEG signals as an objective criterion can enable earlier and proper diagnosis and treatment for some patients who might be overlooked or undiagnosed in interview-based diagnoses, provided that the applications built upon this are mature, stable, and highly accurate. Figure 2 showed the performance at different bands.

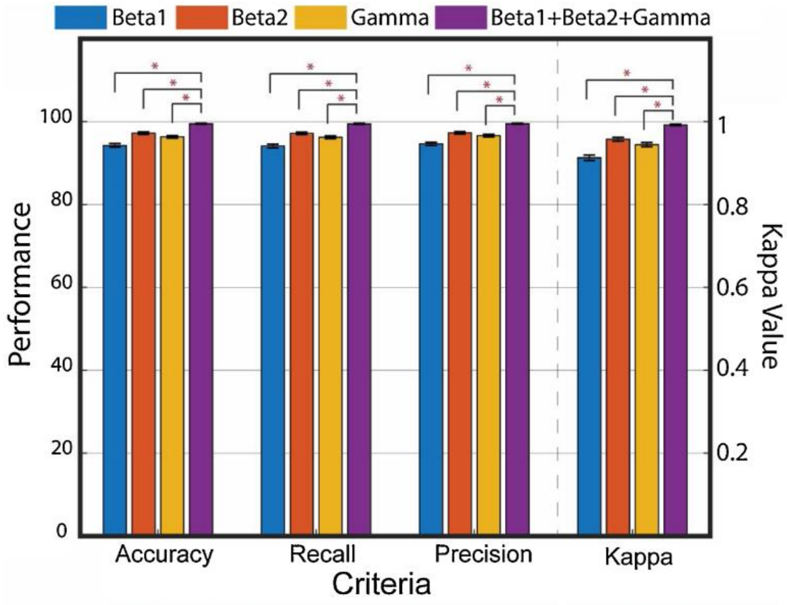

Fig. 2 The proposed method's performance was assessed for individual (β1, β2, γ) and combined frequency bands using Accuracy, Recall, Precision, and Kappa metrics [15]

3. Discussion

Reviewing the performance of deep learning in analyzing EEG for studying ADHD, this paper identifies certain shortcomings and gaps in current research. Firstly, in terms of data selection, most existing studies collect data from untreated/medication-free children, overlooking adolescents and adults with ADHD. While considering that patients' conditions and brain structures become more complex as they grow, and the correlation between data and ADHD is susceptible to the influence of other comorbidities and injuries, adults with ADHD remain a significant aspect for society. Therefore, more data collection and research specifically targeting adult ADHD patients should be conducted in the future. Additionally, given that ADHD is a neurodevelopmental disorder, long-term longitudinal data collection and research analysis on ADHD patients will contribute significantly to the overall study of ADHD, providing a broader perspective and possibilities.

On the other hand, there is a scarcity of existing publicly available data resources, which is not conducive to deep learning models requiring extensive annotated datasets to enhance training effectiveness. It can be observed that most of the current relevant research uses private data, and there is limited research focused on public datasets for analysis. For deep learning to continue playing a role in the direction of ADHD classification, there is a need for more standardized and publicly available datasets to be collected.

Furthermore, the discussion on how to process EEG data to make it more suitable for deep learning training is a topic worth exploring. The innovative approach proposed by Chen et al., involving the transformation of EEG data into an adjacency matrix, is one such method [21]. Unlike straightforward two-dimensional image data, EEG signals possess unique complexities. The intricate network connections among multiple channels make it challenging to simplify them into a two-dimensional format easily. More methods that are better suited for compressing and handling EEG signals in the context of deep learning are anticipated.

In terms of model interpretability, there is significant room for development. ADHD, as a mental disorder, requires diagnostic tools that are frequently used in clinical settings. This implies that any form of model needs to possess interpretability to complement the work of medical professionals. Exploring interpretative methods such as convolutional visualization in the analysis process of deep learning is a possible approach to address this issue.

Simultaneously, tracking and analyzing changes in EEG signals before and after medication or treatment for patients is a promising area. This aspect of research is currently underexplored, and with further investigation and investment, it may assist clinicians in assessing patients' medication responses and developing more effective treatment plans. Given that patients' subjective experiences and expressions may not always be clear or fully align with their objective conditions, objective physiological indicators like EEG can significantly aid doctors in evaluating the effectiveness of current diagnosis and treatment.

4. Conclusion

This review provides a comprehensive overview of ADHD from various perspectives, including epidemiology, neuropsychology, and genetics. Summarizing relevant research, many studies have chosen EEG signals as a preferred physiological indicator, demonstrating superior performance in ADHD detection and classification compared to other physiological signals such as MRI and ECG. From an automation perspective, deep learning models capable of self-learning EEG signal features emerge as a promising choice. Although ADHD research is not a new topic, and deep learning has been widely applied for its excellent performance in various domains, the specific focus on using deep learning to analyze EEG signals for ADHD detection and classification is still in its early stages. Many effective models in this domain have been proposed in recent years. Considering the growing attention to ADHD and the promising prospects of deep learning, exploring the integration of these two fields with EEG signals presents a topic worthy of further investigation and consideration.

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