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Enhancing ADHD Diagnosis: Insights from Data-Driven Classification Approaches

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***Abstract* - Attention-Deficit/Hyperactivity Disorder (ADHD) is a neurodevelopmental disorder marked by persistent patterns of inattention, hyperactivity, and impulsivity that disrupt normal development and daily functioning. These symptoms typically appear in early childhood and can significantly hinder social, academic, and occupational performance. Although early and accurate diagnosis is essential for effective management, it remains challenging due to overlapping symptoms with other conditions and variability in individual assessments. This review paper examines the use of Deep Learning (DL) algorithms in the early detection, classification, and analysis of ADHD. This paper highlights how DL-based approaches can overcome diagnostic limitations, enhance accuracy, facilitate the development of personalized treatment plans, and streamline clinical workflows.**

Index Terms— ADHD classification, Deep learning, Early diagnosis, Neurodevelopmental disorders.

I. INTRODUCTION

Over the past two decades, Attention-Deficit/Hyperactivity Disorder (ADHD) has affected people of all ages worldwide. This prevalent neurodevelopmental disease is typified by recurrent patterns of impulsivity, hyperactivity, and inattention that initially manifest in childhood. A person's social life, schooling, and employment may all be hampered by these symptoms. Since ADHD frequently co-occurs with other disorders including anxiety, depression, or learning disabilities, diagnosing and treating it can be difficult. Focus, organization, time management, and prolonged immobility can all be difficult for those with ADHD. There are three primary types of symptoms, with varying degrees of severity: mostly hyperactive-impulsive, primarily inattentive, or a combination of both [1]. ADHD often runs in families and is thought to have a strong genetic component. However, it may also develop as a result of environmental factors like stress or exposure to contaminants during pregnancy. Recent developments in brain imaging studies have demonstrated that the structure and function of specific brain regions, especially those involved in attention and impulse control, differ in people with ADHD. Adults with ADHD sometimes go undiagnosed or untreated, despite the fact that it is frequently recognized in children. Nonetheless, increased public knowledge and education on ADHD have lessened stigma in recent years, motivating more people to get aid and treatment [2].

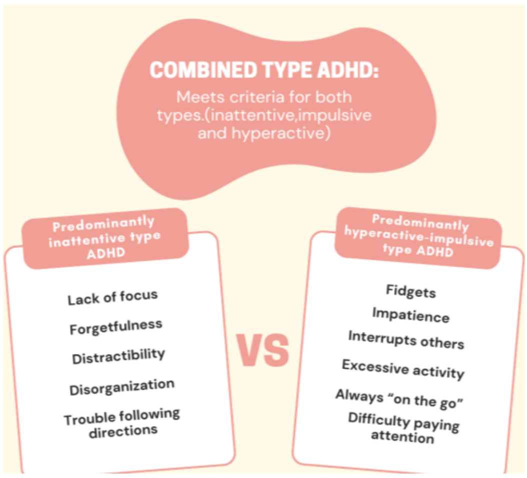

Fig 1: Differentiation of hyperactive ADHD and inattention ADHD and its common traits

The precise etiology of ADHD is still unknown, but a mix of environmental, neurological, and genetic factors are thought to be responsible. According to research on brain imaging, people with ADHD can have variations in the composition and functionality of specific brain areas. ADHD can be successfully controlled using a variety of strategies, even if it cannot be totally cured. These include of behavioral treatment, educational support, regular routines, and drugs like stimulants and non-stimulants.

Deep learning has the potential to greatly improve the diagnosis and understanding of Attention-Deficit/Hyperactivity Disorder (ADHD). Subjective observations and behavioral evaluations are the mainstays of traditional diagnostic techniques, which can be laborious and imprecise. Through the use of deep learning algorithms to analyze vast and intricate datasets, including behavioral patterns, genetic data, and brain imaging, researchers may be able to spot minor indicators of ADHD that traditional approaches could miss. This could lead to earlier and more accurate diagnoses, ultimately improving disease management [3].

Neural networks, a key deep learning technique, have shown particular promise in analyzing neuroimaging data, including Electroencephalogram (EEG) scans and functional Magnetic Resonance Imaging (fMRI). These models can detect slight differences in brain structure and activity associated with ADHD, helping to distinguish it from other conditions with similar symptoms. Additionally, by identifying individual variations in brain connectivity, researchers can gain valuable insights into the neurological basis of ADHD and its link to symptoms such as hyperactivity and inattention. Figureure 1 display about the differentiation of hyperactive ADHD and inattention ADHD and its common traits.

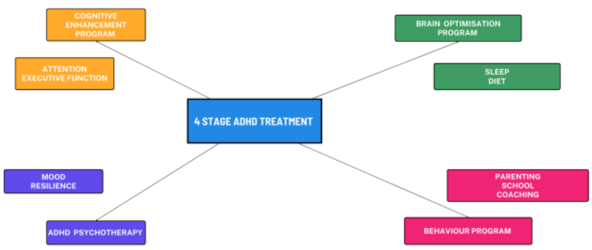

Fig 2: Four stages of ADHD treatment program

Analysis of sizable patient datasets, such as genetic markers, clinical history, and therapeutic response patterns, can also play a crucial role in improving ADHD treatment by helping to predict the most effective treatment plans for each patient. Better patient results could result from this individualized approach, which could increase the effectiveness of therapy like behavioral interventions and drugs [4]. Figure 2 shows the four different stages of ADHD treatment program. Overall, deep learning offers fascinating chances to improve our knowledge and treatment of ADHD, paving the way for more specialized and effective therapies. However, optimizing these algorithms requires complex model architectures, and the results are not always consistent. Therefore, this paper aims to explore and review ADHD research by analyzing recent medical literature on the subject.

II. Related Works

Attention deficit hyperactivity disorder (ADHD) is a condition that affects people's behaviour. People with ADHD can seem restless, may have trouble concentrating and may act on impulse. Many real-time practices have adopted various Deep Learning (DL) technologies in the detection and classification of ADHD. Few of those research studies have achieved promising results, but still they are not enough for the long-term.

For instance, in 2022, Garcia-Argibay et. al. [5] have proposed deep learning technique to predict the beginning of attention-deficit/hyperactivity disorder in children and adolescents, due to its complexity and the existence of mental and medical Disorders, Attention-Deficit/Hyperactivity Disorder (ADHD) disease in children and adolescents can be difficult to diagnose. In order to increase the accuracy of diagnosing ADHD, a research including 238,696 Swedish people have the DNN model performed better than the others, with an AUC of 0.75 and balanced accuracy of 0.69. At a threshold of 0.45, the specificity was 65% and the sensitivity was 71.66%. It was beneficial to physicians.

In 2024 Nizar Alsharif et al. [6] have presented a study of using deep learning to diagnose ADHD, the analysis of electroencephalograms (EEGs) and the categorization of brain illnesses have received a lot of attention lately. This study introduces deep learning (DL) frameworks that use an EEG-based brain network. The accuracy and efficacy of diagnosing ADHD can be greatly increased by integrating objective diagnostics into the diagnosis procedure. A public EEG datasets from 60 children with normal development and 61 children with ADHD were utilized in the study. Preprocessing was done on the raw EEG data, which included notch filters and filtering in clinically important frequency ranges. The preprocessed segments were used to extract statistical and spectral properties including entropy, kurtosis, and standard deviation.

Liu et al. [7] reviewed several studies on ADHD in 2024, covering subjects such as prevalence, pathological reasons, patient challenges, and popular treatments. It also discusses studies that employ technology to pinpoint the physiological signs of ADHD. By providing a summary of the literature on the pathogenic origins and subtype variations of ADHD, the first section offers a theoretical basis for the use of EEG data in ADHD analysis. The second section focuses on distinguishing EEG signals between individuals with ADHD and its subtypes and those who are typically developing. It illustrates how deep learning models for automated diagnosis may be trained using these physiological inputs.

Wonjun Lee et al. [8] stated Screening Game in 2023, which identified children's abnormal behaviors in the robot-led ADHD screening game by employing a bidirectional LSTM-based deep learning model to classify ADHD and ADHD-RISK. The normal and ADHD categories are often distinguished in previous studies on ADHD categorization. A projection-based game that lets players see inputs and reactions has been developed as a solution to this problem, supporting to better understand children's abnormal behavior. In the eleven stages of the screening game, kids play five games. Since every game includes both an active gameplay stage and a waiting stage, we could gather data at various points in time. Based on skeletal data collected during these times, we classified children into normal, ADHD–RISK, and ADHD groups using a bidirectional LSTM-based deep learning model. For each of the three classes, the model's classification accuracy was 98.15%.

In 2024 Javier Sanchis et al [9] have proposed a disease detection system using EEG, with a Multi-scale Deep Learning Convolutional Neural Network. This technique introduces EEG-MSC Net, a Deep-Learning Multi-scale Convolutional Neural Network designed specifically to tackle the ADHD disease. This newly proposed approach improves the reliability and effectiveness of comparison child methodologies by automating feature extraction and processing. To guarantee robustness and generalizability, a Leave-One-Out subject cross-validation technique was used. By using this validation method, the danger of over-fitting is reduced and the model's performance on unseen subjects is guaranteed. The findings open the door for more dependable and automated diagnostic options by demonstrating EEG-MSCNet's potential as a useful tool for precise ADHD diagnosis.

In the same year, Sumbul alam et al [10] have introduced a Human Activity Recognition (HAR) in real time using a deep learning system, cameras may be used to predict meltdown situations in people with autism and ADHD in real time. In extreme cases, such level 3 autism, sudden meltdowns are prevalent and can endanger the child and everyone around them. Children with ASD exhibit certain behaviors that are suggestive of violent outbursts, according to studies. These situations are challenging for caregivers, which emphasizes the need for effective intervention strategies.

The goal of this research is to create a convolutional neural network based real-time HAR system that can identify pre-meltdown behaviors. The suggested method creates a dataset with two behavior classes by using camera input to recognize typical movements connected to meltdowns. In the future, a bigger dataset, like HMBD51, will be built into the algorithm to improve its capacity to identify a variety of gestures and forecast meltdowns in a range of brain illnesses. With a good frame processing speed (FPS) and 100% training correctness, the present model shows encouraging results. With every time, the accuracy of validation keeps getting better. This approach is a useful tool for treating neurodevelopmental problems since it may notify caregivers of impending meltdowns, reducing self-harm and guaranteeing prompt action.

In the year 2020, Jee-Won Song and others [11] conducted the study on Deep Learning Using Neuroimaging in Attention-Deficit/Hyperactivity Disorder and Autism Spectrum Disorder, Artificial Intelligence to find patterns in data and effectively evaluate big datasets for classification and prediction tasks. Numerous signs have been investigated for diagnosis, categorization, prognosis prediction, and therapy response in neuroimaging for neurodevelopmental disorders. These signs have not been successfully combined, nevertheless, to provide insightful information.

By combining DL with neuroimaging, researchers can harness the full potential of these signs to improve clinical decision-making. This review explores studies that integrate DL with neurodevelopmental disorder neuroimaging, discussing the strengths, challenges, and future directions in this emerging research field. It highlights how DL can advance our understanding and improve the clinical application of neuroimaging for these disorders.

In 2023 [12] Amado-Caballero at al. data augmentation (DA) improves the performance of Convolutional Neural Network (CNN) models. For accurate ADHD screening, this approach is essential. Early detection of ADHD is made possible by the use of the ADHD-200 Dataset, fMRI images, classification methods, and feature selection modules. This allows for prompt therapies.

In another study done by Nina de Lacy at al [13] Using optimal de adolescence common externalizing illnesses that rise in late childhood and predict adult psychopathology include ADHD, oppositional defiant disorder (ODD), and conduct disorder (CD). Diagnostic overlap makes intervention planning more difficult, even though it is curable. Finding variables that differentiate ADHD from ODD and CD is essential in early adolescence in order to inform successful therapies. In order to predict the start of ADHD, ODD, and CD at a 2-year follow-up, this study examined 5,777 multimodal variables from the ABCD cohort, including demographics, academics, medical history, psychosocial factors, and brain measurements.

An AI-based approach for feature selection and model training using deep learning yielded an accuracy of around 86-97% and an AUROC of 0.919-0.996. With neural-only characteristics, predictive performance decreased to about 80%. Important predictors were parent behavioral traits, sleep problems, and school performance; MRI measurements of the limbic system were especially linked to the onset of CD. In addition to highlighting unique variables for each illness, multimodal AI models showed excellent accuracy in forecasting externalizing disorders. While structural MRI measurements were effective in identifying the onset of CD, psychosocial markers proved to be important across various conditions. The study offers insights for developing targeted interventions and underscores the importance of using comprehensive data in constructing reliable prediction models. To enhance generalizability, future research should aim to replicate these findings using additional datasets.

In 2020, Tjhin Wiguna et al. [14] explored the use of virtual reality (VR) as a tool to support ADHD diagnosis. VR offers realistic simulations that can engage children in enjoyable and low-stress environments, replicating everyday settings where attention and behavior can be observed more naturally. These simulations have the potential to improve the sensitivity and accuracy of ADHD assessments, particularly in regions with limited access to mental health services or tele-consultation. Although some VR-based continuous performance tests (VR-CPT) have been developed for ADHD, they are not yet widely available. Simplifying the diagnostic process and refining the design of VR tools can enhance both the accuracy and practicality of these systems.

The study also discusses the development of a VR diagnostic game prototype for ADHD, based on a clear four-step framework, aimed at making the assessment process more accessible and efficient, especially in underserved or remote areas. Qualitative and quantitative methods are combined in this mixed-method research approach to increase the reliability of the results. The proposed method ensures the tool's accuracy and transparency, addressing the need for innovative and reliable diagnostic solutions in ADHD management.

In 2022, Dingfu Zhou and others [15] conduct the study using the electrical activity of neurons from intracranial or scalp sources, is frequently utilized. Ambulatory EEG and long-range video EEG are the two main techniques for long-range EEG monitoring, and both are essential for diagnosis. This study uses long-range video EEG data to examine the clinical features and brain activity of children with ADHD. It examines the therapeutic relevance of this method in diagnosing ADHD and offers insights into the electrical patterns of the brain. The study takes the video data and builds several deep learning-based neural networks to improve analysis.

III.RESERCH GAPS

Although the amount of research carried out on the ADHD is increasing, still, there are gaps. Diagnostic tools are subjective and fail to bring together various data sources critical to making a diagnosis including neuroimaging and genetic data. Under diagnosis of ADHD and late-onset ADHD must be treated in a gender-sensitive manner. Figure 4 explains regarding the numerous difficulties experienced in the disease diagnosis process of ADHD. Moreover, the study on the latest model of neural networks such as transformers and long-range EEG analysis has yet to be studied, and further emphasis has to be provided to ensure that the experiment can be applied on a more effective and culturally-sensitive diagnostic tool.

Indicatively, research by Lee, Wonjun, et al. [8] shows the difficulty in classifying the ADHD-RISK as it is a less explored classification that is quite challenging when it comes to its differentiation in a clinical setting. It is important to build the deep learning (DL) models that could optimize the diagnostic evaluations and help to diagnose ADHD-RISK and assist the making of clinical decisions. Also, inclusion of the skeletal data of children into interactive screening games may increase the accuracy of the diagnosing. Nevertheless, the use of these DL methods is unexploited in the classification of ADHD and thus it is worth exploring in the future.

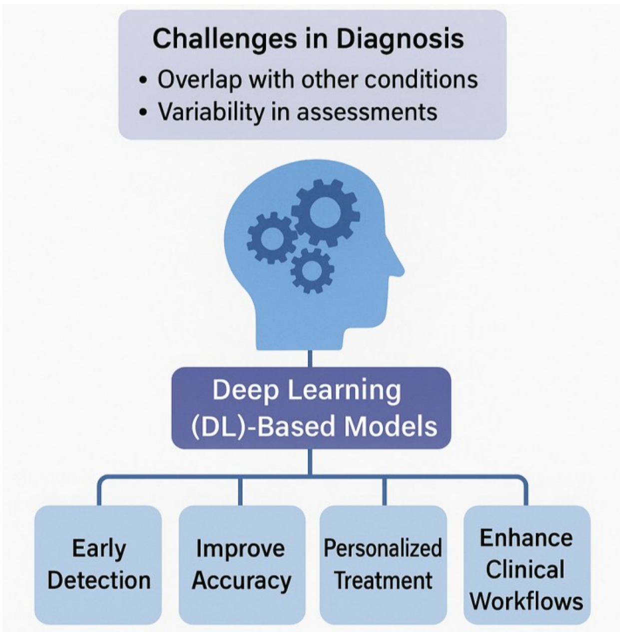

Fig 3 : Challenges in ADHD Diagnosis

Recently, Khairul Islam [16] conducted a pertinent research by noting that a great gap exists on multifunctional data collection in ADHD diagnosis, such as measuring EEG signals on behalf of behavioral/genetic/neuroimaging data. The use of multipurpose methods would allow determining the correct diagnosis and gaining better insights into ADHD manifestations. The Attention-deficit/hyperactivity disorder: new approaches toward is presented in the Figure 3. One of the key challenges in clinical practice is accurately identifying rare ADHD cases, which are often difficult for physicians to diagnose. More advanced methods are needed to distinguish between ADHD and ADHD-RISK in order to support more accurate clinical decision-making. Additionally, there is limited research on incorporating novel data sources such as children's skeletal movement data from ADHD screening games into diagnostic approaches. Future studies should aim to refine analytical techniques, improve the clarity of diagnostic criteria, and include more diverse datasets to address these gaps [17]. Achieving greater diagnostic accuracy and promoting fair classification of ADHD remain essential objectives. These challenges are among the most frequently noted by researchers working in this area.

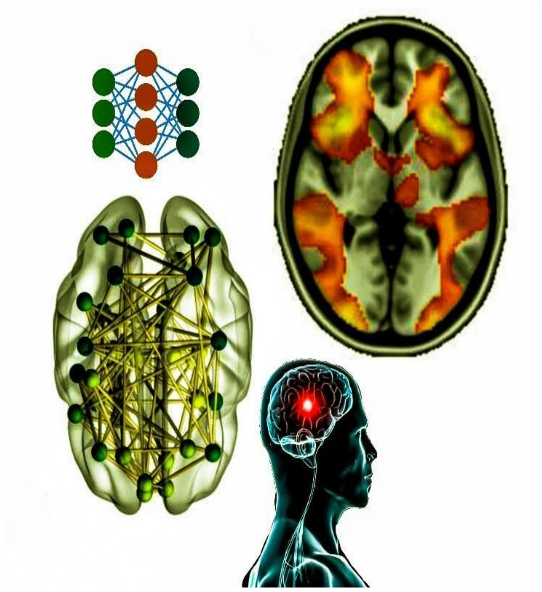

Fig 4: Attention-deficit/hyperactivity disorder: new approaches toward understanding the neural mechanisms

The real-time use of ADHD diagnostic tools in realistic environments, such classrooms or telemedicine platforms, is another unexplored field that calls for low-latency, adaptive models that can handle real-time data streams. Another recurring problem is gender inequality in training datasets, as most models are trained primarily on male participants, ignoring the distinct behavioral patterns frequently seen by females with ADHD. Additionally, despite the fact that data augmentation is frequently employed in picture classification tasks, model generalization is limited by the lack of reliable augmentation techniques designed especially for EEG or fMRI data. Finally, despite its promise to secure sensitive patient data and facilitate collaboration across clinical institutions, the potential of federated learning-a privacy-preserving technique that permits model training across decentralized datasets-has not been adequately investigated in ADHD research.

IV. CONCLUSION AND FUTURE WORKS

There is great potential in ADHD detection process improvement level. This review article focuses on the question of the effectiveness of the advanced diagnostic methods in the individual diagnosis of the ADHD condition that needs to be evaluated timely and correctly. As the results show, some of the newer techniques tend to be more accurate, efficient, and fast in classifications as compared to traditional methods of diagnosis. These techniques enable the identification of faint trends and rudimentary developments of ADHD that could be hard to identify by using conventional clinical assessment by leveraging huge and heterogeneous datasets. Combining several types of data- e.g., clinical history and imaging evaluation- can take ADHD diagnosis even further by increasing accuracy and reliability. The validity of these strategies however depends much on the quality of the data consulted. Data collection differences, information gaps and differences in the ways the datasets have been shaped, may all influence the results of the diagnosis. There are practical issues with integrating DL into the current clinical workflow, and this requires immense efforts to make the systems compatible and also train the associated healthcare professional effectively. The way forward would be to concentrate on cost-efficient data gathering, multimodal integration, and gender and age-specific models, scale personalized solutions, and explainable AI to create accurate, inclusive, and culturally adjustable ADHD diagnostics.

Furthermore, this work identifies enduring gaps in multimodal fusion techniques by categorizing and contrasting previous studies across many data modalities (fMRI, behavioral, skeletal, and EEG). Future ADHD diagnosis systems that are more precise, inclusive, and context-aware could be made possible by addressing these issues. This review not only summarizes recent deep learning applications for ADHD diagnosis but also offers detailed technical breakdowns of each model, enabling a clearer comparison of their real-world feasibility, efficiency, and diagnostic value.

REFERENCES

1. Chugh, N., Aggarwal, S., & Balyan, A. (2024). The hybrid deep learning model for identification of attention-deficit/hyperactivity disorder using EEG. Clinical EEG and Neuroscience, 55(1), 22-33.
2. Han, M., Jin, G., & Li, W. (2024). Assessment of Attention-based Deep Learning Architectures for Classifying EEG in ADHD and Typical Children. International Journal of Advanced Computer Science & Applications, 15(3).
3. Firouzi, M., Kazemi, K., Ahmadi, M., Helfroush, M. S., & Aarabi, A. (2024). Enhanced ADHD classification through deep learning and dynamic resting state fMRI analysis. Scientific Reports, 14(1), 24473.
4. Zaheer, A., & Akhtar, A. (2025). Artificial intelligence as a support to diagnose ADHD: an insight of unorthodox approaches: a scoping review. Child Neuropsychology, 1-35.
5. Garcia-Argibay, M., Zhang-James, Y., Cortese, S., Lichtenstein, P., Larsson, H., & Faraone, S. V. (2023). Predicting childhood and adolescent attention-deficit/hyperactivity disorder onset: a nationwide deep learning approach. Molecular Psychiatry, 28(3), 1232-1239.
6. Alsharif, N., Al-Adhaileh, M. H., & Al-Yaari, M. (2024). Diagnosis of attention deficit hyperactivity disorder: A deep learning approach. AIMS Mathematics, 9(5), 10580-10608.
7. Liu, X. (2024). Detection and Classification of ADHD Using Deep Learning Based on EEG Signals. Highlights in Science, Engineering and Technology, 91, 191-199.
8. Lee, W., Lee, S., Lee, D., Jun, K., Ahn, D. H., & Kim, M. S. (2022). Deep Learning-Based ADHD and ADHD-RISK Classification Technology through the Recognition of Children's Abnormal Behaviors during the Robot-Led ADHD Screening Game. Sensors, 23(1), 278.
9. Sanchis, J., Kechadi, T., Teruel, M. A., & Trujillo, J. (2024). Multiscale Deep Learning Convolutional Neural Network for ADHD Detection using EEG.

10. Alam, S., & Raja, S. P. (2024). Predicting meltdown situation in Autism and ADHD in real-time through camera using deep learning algorithm. Journal of Electrical Systems, 20(3), 1631-1639.

11. Song, J. W., Yoon, N. R., Jang, S. M., Lee, G. Y., & Kim, B. N. (2020). Neuroimaging-based deep learning in autism spectrum disorder and attention-deficit/hyperactivity disorder. Journal of the Korean Academy of Child and Adolescent Psychiatry, 31(3), 97.

12. Amado-Caballero, P., Casaseca-de-la-Higuera, P., Alberola-López, S., Andrés-de-Llano, J. M., López-Villalobos, J. A., & Alberola-López, C. (2023). Insight into ADHD diagnosis with deep learning on Actimetry: Quantitative interpretation of occlusion maps in age and gender subgroups. Artificial Intelligence in Medicine, 143, 102630.

13. de Lacy, N., & Ramshaw, M. J. (2023). Identifying selective predictors of ADHD, Oppositional Defiant and Conduct Disorder onset in early adolescence with optimized deep learning. medRxiv, 2023-08.

14. Wiguna, T., Wigantara, N. A., Ismail, R. I., Kaligis, F., Minayati, K., Bahana, R., & Dirgantoro, B. (2020). A four-step method for the development of an ADHD-VR digital game diagnostic tool prototype for children using a DL model. Frontiers in Psychiatry, 11, 829.

15. Zhou, D., Liao, Z., & Chen, R. (2022). [Retracted] Deep Learning Enabled Diagnosis of Children's ADHD Based on the Big Data of Video Screen Long-Range EEG. Journal of Healthcare Engineering, 2022(1), 5222136.

16. Islam, K. (2024). Enhancing ADHD Diagnosis Using Deep Learning: A Robust Model for Analyzing EEG Signals in Children. J. Electrical Systems, 20(3), 4806-4817.

17. Lee, W., Lee, D., Lee, S., Jun, K., & Kim, M. S. (2022). Deep-learning-based ADHD classification using children's skeleton data acquired through the ADHD screening game. Sensors, 23(1), 246.