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Detecting Attention Deficit Hyperactivity Disorder (ADHD) Inflicted Humans using Long Short-Term Memory (LSTM)

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Abstract: ***Attention Deficit Hyperactivity Disorder (ADHD) is a common psychiatric disorder characterised by persistent patterns of inattention, hyperactivity, and impulsivity in children. The risk factor is that these children are frequently entangled in learning difficulties, which lead to frustration when they reach adulthood. This study uses functional Magnetic Resonance Imaging data for the resting-state brain to present an effective approach for ADHD identification at an early stage. The proposed method is based on seed correlation, which calculates the functional connectivity between seeds and all other voxels in the brain.This paper gives a walk through of the steps for using machine learning to analyse rs-fMRI data and, more specifically, to distinguish Attention Deficit Hyperactivity Disorder (ADHD) from healthy controls. I discuss (1) feature extraction with masks, (2) the advantages and disadvantages of long short term memory networks (LSTM) for classifying fMRI data, and (3) hypothesis testing and its application in model evaluation.***
Keywords: ADHD, f-MRI, Impulsive behaviour, Anxiety, LSTM

I. INTRODUCTION

ADHD is a common behavioural pattern characterised by inattention, hyperactivity, and impulsivity that occurs at a higher rate than in the general population [1]. At the moment, 7% of the world's population has been diagnosed with ADHD, including 6.4 million children aged 7 to 14 in the United States. ADHD is a common neurodevelopmental mental disorder that affects 5-10% of the child population, resulting in a poor quality of life and lifetime impairment [2]. As a result of a lack of appropriate therapies, a higher proportion of ADHD children will continue to have clinical symptoms into adulthood, displaying destructive elements [2]. Hyperactivity can also manifest itself in other areas, such as creativity and curiosity, in which inattentive and impulsive children excel. With a lack of proper treatments, there is a high risk of these behaviours and symptoms developing into comorbid disorders such as conduct disorder, obsessive-compulsive disorder, and other learning-related difficulties [3]. Recent studies [3][4] have also revealed that abnormalities in various brain areas such as the anterior cingulate posterior cingulate cortex and ventromedial prefrontal cortex are the main causes of this disorder. According to regional homogeneity analysis [5,] there are significant differences in activity in the cerebellum, motor cortex, and temporal lobe in ADHD positive subjects. The diagnosis of ADHD indicates that these areas are required when analysing functional Magnetic Resonance Imaging (fMRI) data. ADHD in clinical practise has sparked interest in research into accurate ADHD identification. The lack of well-defined techniques for diagnosing ADHD in clinical practise has prompted research into accurate ADHD identification. The study explains how to use the LSTM model to distinguish ADHD patients from healthy controls using rs-fMRI. The paper goes on to discuss hypothesis testing and shows how it can be useful in a diagnostic experiment.

II. RELATED WORK

Name of the paper: “Machine Learning Methods for Diagnosing Autism Spectrum Disorder and Attention-Deficit/Hyperactivity Disorder Using Functional and Structural MRI: A Survey”
Authors: Taban Eslami, Fahad Almuqhim, Joseph S. Raiker and Fahad Saeed
In this paper they have summarize recent progress in machine learning model for diagnosis of Attention-deficit/Hyperactivity Disorder (ADHD). They outline and detail the machine-learning, particularly deep-learning, techniques that are suitable for addressing research questions in this domain, pitfalls of the currently available methods and along with these, future directions for the same.

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They envision a future where the diagnosis of ASD, ADHD, and other mental disorders is accomplished, and measured using imaging techniques, such as MRI, and machine-learning models. The paper will give a broad overview of the existing techniques for ADHD classification and will lead neuroscientists through the methodology for the design and execution of these models.

Name of the paper: "Automatic Extraction and Detection of Characteristic Movement Patterns in Children with ADHD Based on a Convolutional Neural Network (CNN) and Acceleration Images"

Authors :Mario Muñoz-Organero ,Lauren Powell, Ben Heller and Val Harpin Jack Parker**.**

This paper focuses on analyzing the data obtained from two tri-axial accelerometers worn during school hours by a group of 22 children. Out of the 11 ADHD diagnosed children, 5 were not on medication during the study. The children were not explicitly told to do any activity but instead followed a typical session at school; alternating classes of little or moderate physical activity with intermediate breaks of more intense physical activities. The tri-axial acceleration signals were transformed into 2D acceleration images, and a Convolutional Neural Network (CNN) was trained to distinguish between non-medicated ADHD children and their paired controls. An accuracy of 0.875 for the wrist sensor and 0.9375 for the ankle sensor was reached using a Convolutional Neural Network (CNN) to automatically extract embedded acceleration patterns and provide an objective measure to aid in the diagnosis of ADHD.

III. PROPOSED SYSTEM

A. Dataset

With Nilearn, many advanced machine learning, pattern recognition, and multivariate statistical techniques for neuroimaging data in applications such as MVPA (MultiVoxel Pattern Analysis), decoding, predictive modeling, functional connectivity, brain fragmentation, and Connectome, can be easily applied. Nilearn is easy to use for task fMRI, hibernate, or VBM data. For machine learning professionals, the value of nilearn can be seen as a domain-specific, functionally designed structure. H. Shapes neuroimaging data into a feature matrix suitable for statistical learning and vice versa.

To detect ADHD, this project gets an fMRI dataset from Nilearn. The dataset contains 100 subjects and is already preprocessed and ready for use. Group-level analysis common in fMRI is based on a general linear model and consists of a univariate method. This study introduces a spatially constrained local multivariate model for group-level analysis to increase sensitivity with specific specificities in activation detection.

B. Understanding and Preprocessing of Data

fMRI images are 4D matrices that depict each voxel's activation level in three-dimensional space and time. A subset of this data is frequently used to represent the relevant information. This system is only curious about the resting state networks so to omit the irrelevant data, masks are applied. Masks are simply filters that allow only a subset of data to pass while rejecting the rest. Unwanted voxels' activation values are set to 0 via masks. There are many ways to mask fMRI data, but it is primarily determined by the purpose of the analysis. The system focuses on classifying ADHD patients and controls over the resting network. Therefore, Smith's rsfMRI component atlas (Smith et al., 2009) is used. Smith Atlas reflects 70 Resting Networks (RSNs) collected using Independent Component Analysis (ICA) from thousands of healthy patients.

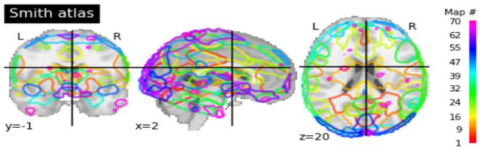


Figure 1. From the header of the first image, we see that the image contains 73*61*61 voxels over 176 timestamps. Additionally, each voxel is about 3mm³.

To mask the data, the system generates the mask from the Smith`s atlas. Applying a standardization can contribute to the features` robustness. It helps in enhancing the signal by centering and normalizing the slices for each timeseries. Considering the data confounds as part of the transformation process can also help to enhance the signal by removing confounding noise. The dataset might not hold a homogenous scanning length However, most machine learning algorithms (Keras included) require a uniform shape across all subjects. Padded to optimize data storage. Add zeros to each subject after the scan is complete to match the length of the longest scan. In addition to padding, the system reshapes the data to meet Keras requirements.

IV. ALGORITHM

Long short-term memory (LSTM) models offer several advantages when learning from fMRI data. The main reason for this is that unlike most machine learning and deep learning methods, it can retain input context information. That is, during the processing of the current sequence, the details from the previous part of the input sequence are included. Due to the nature of the context, we decided to demonstrate the ability of LSTMs in fMRI analysis**.** Because fMRI data represent dynamic brain activity over time, LSTMs can be used to leverage time information (which would otherwise have been lost) **in** functional connectivity analysis (Dvornek)**.** et al., 2017).

A common extension of LSTMs is the use of convolutional neural networks (CNNs) that support the analysis of spatial structures. However, we have abandoned the spatial properties of the data because we have extracted 70 individual values that reflect the independent components of network-wide activation. Therefore, CNN is probably useless.

A common regularization in LSTM networks is a dropout, which stochastically excludes units from layer connections. There are two types of dropouts: input dropouts and regular dropouts. Input failure means that there is a certain probability that data about the input connection to each LSTM entity will be excluded from node activation and weight updates (see Failure Arguments). Dropouts on repetitive inputs work the same**,** but on repetitive connections (see argument recurrent_dropout). However, it is important not to over-regulate. This prevents the model from being trained first (it can be detected by strict non-index prediction). The model presented here is a sequential model with three stacked LSTM layers and one high density layer with sigmoid activation.

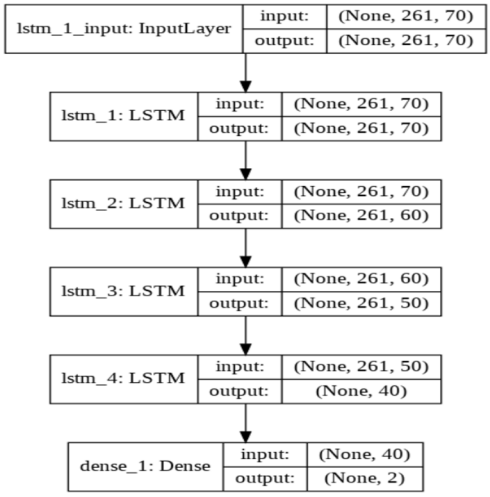


Figure 2:some increase in the model's accuracy and some decrease in the model's loss as the number of epochs increases.

Evaluate the model using the Hypothesis Testing Framework to help determine both the accuracy of the model and its importance. Use the bootstrap to calculate the importance of the model. In short, bootstrap is a powerful computational method for statistical inference without relying on too many assumptions. This helps to estimate the characteristics of the population by making estimates from **a** small sample of the data. The ROC curve reflects the sensitivity and specificity of the model by plotting the true positive rate and the false positive rate. I chose to plot the median (not the mean) of the ROC curve. This is to provide a more robust measurement when the data is distorted.

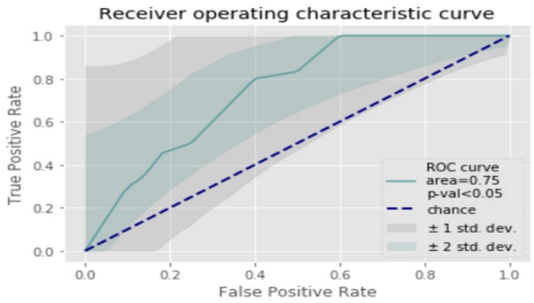


Figure 3:The ROC curve seen above shows a significant above-average classification capacity.

You can see that the median and the SD around **it** are located on a completely random diagonal. The 95% confidence interval (represented by 2 SD around the central ROC curve) extends below the probability diagonal, primarily at the lower left point. This can mean that the model tends to express higher sensitivity**,** but less specificity.

V. GUI

In addition to the algorithm, a graphical user interface is also built into this system. The GUI detects ADHD when the patient details are entered with fMRI. The first look at the GUI has a Check Now button, which you can click to display a form containing details about the patient such as name, age, gender, email, IQ, and the problem you are facing. In addition to filling in the details, you also need to upload the patient's fMRI. Once submitted, the percentage will be used to determine if you have ADHD. The GUI also contains information for those who are new to the site and are unaware of what ADHD is and the symptoms of ADHD. This GUI system is based on the HTML and CSS languages. Using Python's bottle library, algorithms, and HTML, I combined CSS to achieve the desired result.

This system was using multivariate fMRI data to detect ADHD. As we have increased epochs the accuracy increases, and the model gives better results. 1 indicates the patient having ADHD and 0 indicates not. Between 0 and 1 the system tells us what percent changes there of the patient are having ADHD. The train and test of this system has an increasing accuracy of the model.

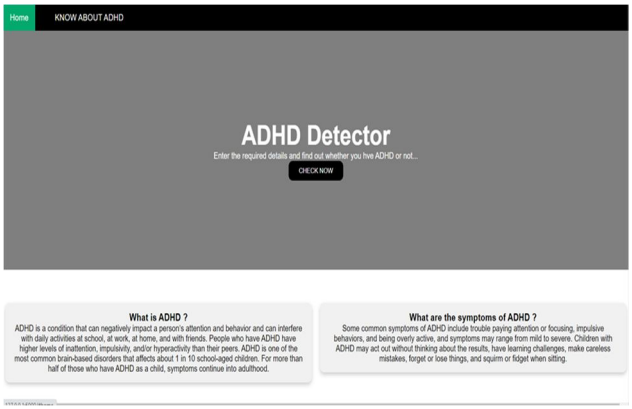


Fig 4. The home page of GUI

On the click of check now button or if scrolled below the system will take to the form.

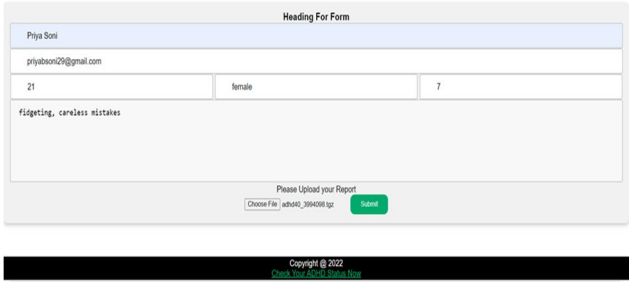


Fig 5. Form filling for detection of ADHD

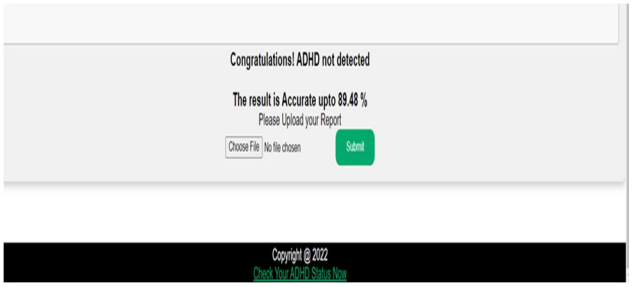


Fig 6. Result of ADHD

VI. RESULT

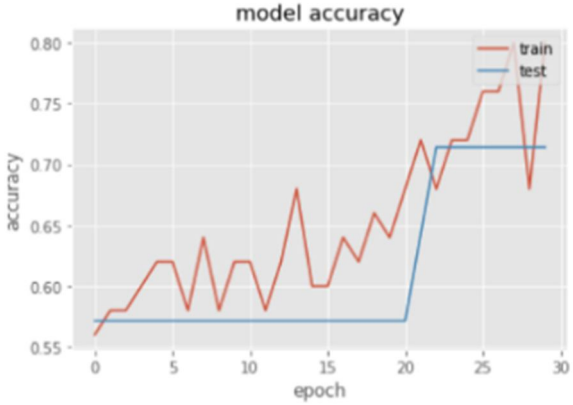


Figure 7. We see some increase in the model's accuracy and some decrease in the model's loss as the number of epochs increases.

The model's sensitivity is the proportion of patients that were identified correctly to have the disease (i.e. True Positive) upon the total number of patients who actually have the disease. The model's specificity describes the proportion of patients that were identified correctly to not have the disease (i.e. True Negative) upon the total number of patients who do not have the disease. Usually, these two display an inverse relation.

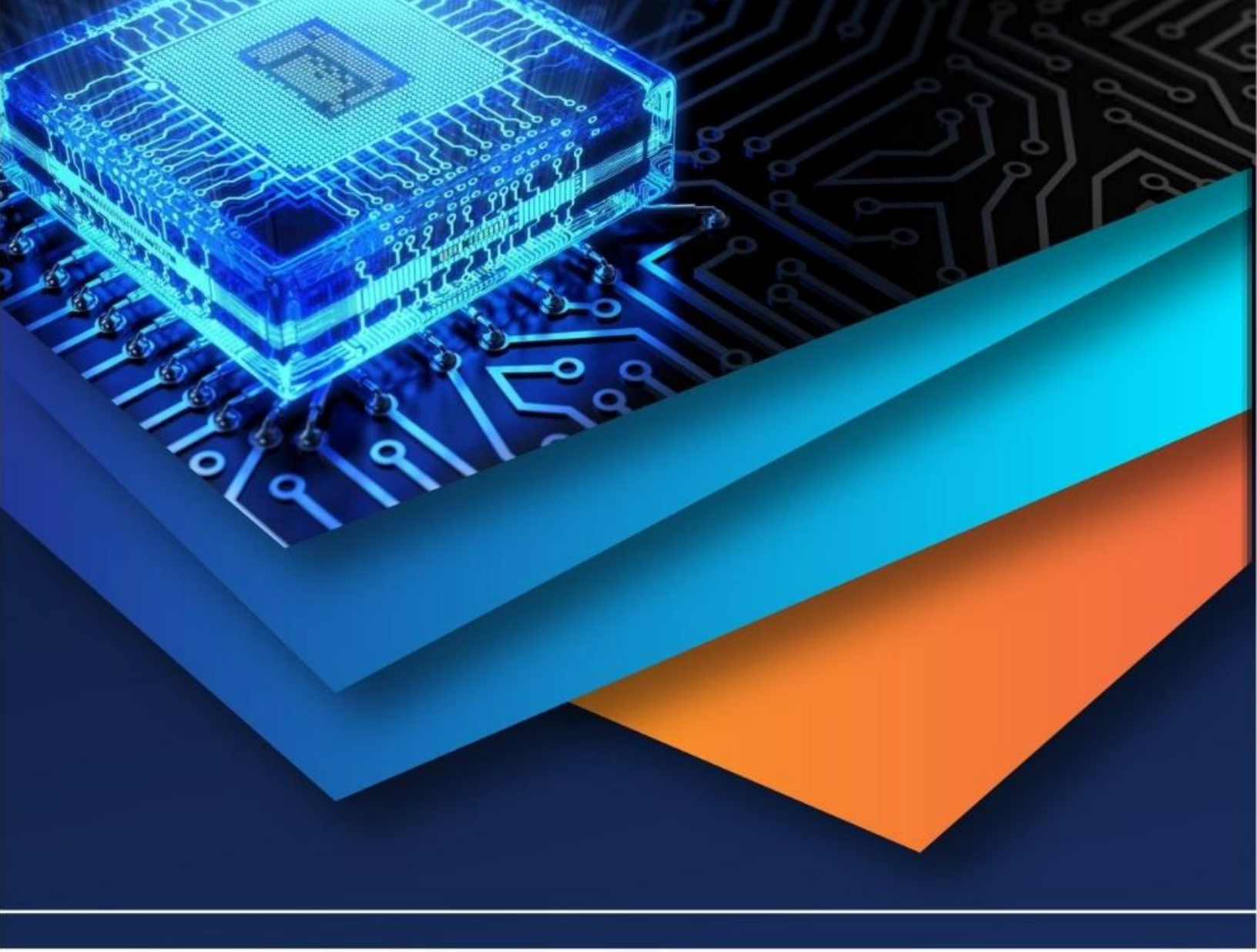
VII. CONCLUSION

LSTM algorithm was used to build a model of detection of ADHD syndrome using fMRI image data. This helps to classify this syndrome early. Studies have revealed how specific communication between different brain regions, known as brain connectivity, can serve as a biomarker for attention deficit hyperactivity disorder (ADHD). It can be used to classify failures using machine learning algorithms. As we learn more about brain health and development, more opportunities will emerge to help young people take care of themselves. We may pay more attention to factors known to promote sleep hygiene, stress management, diet and exercise, and mental health. Overall, awareness of the need to make shared decisions with adolescents and parents remains the key to improving ADHD compliance and optimizing long-term outcomes. This helps physicians better target treatment by understanding where the patient sits in the wide continuum.

REFERENCES

[1] Taban Eslami , Fahad Almuqhim, Joseph S. Raiker and Fahad Saeed ,"Machine Learning Methods for Diagnosing Autism Spectrum Disorder and Attention-Deficit/Hyperactivity Disorder Using Functional and Structural MRI: A Survey",20 January 2021
[2] Behzad Iravani ,Artin Arshamian ,Peter Fransson and Neda Kaboodvand,"Whole-brain modelling of resting state fMRI differentiates ADHD subtypes and facilitates stratified neuro-stimulation therapy" 1 May 2021
[3] Mario Muñoz-Organero ,Lauren Powell, Ben Heller and Val Harpin Jack Parker,"Automatic Extraction and Detection of Characteristic Movement Patterns in Children with ADHD Based on a Convolutional Neural Network (CNN) and Acceleration Images",14 November 2018
[4] Laura Dubreuil-Vall, Giulio Ruffini, and Joan A. Camprodon,"Deep Learning Convolutional Neural Networks Discriminate Adult ADHD From Healthy Individuals on the Basis of Event-Related Spectral EEG **",** 9 April 2021
[5] Andrei A.Puiua Olga Wudarczykb, Katharina S.Goerlichbg, Mikhail Votinovbcd, Beate Herpertz-Dahlmannf, Bruce Turetskye, Kerstin Konrada.Aggression,"IMPULSIVE AGGRESSION AND RESPONSE INHIBITION IN ATTENTION-DEFICIT/ HYPERACTIVITY DISORDER AND DISRUPTIVE BEHAVIORAL DISORDERS.", July 2018
[6] Ane Ann Sedgwick, Andrew Merwood and Philip Asherson."The positive aspects of attention deficit hyperactivity disorder: a qualitative investigation of successful adults with ADHD." 29 oct 2018.
[7] University at Buffalo. "Detecting ADHD with near perfect accuracy: Machine learning model is superior to similar predecessors or traditional behavioral diagnosis, says UB researcher." ScienceDaily. ScienceDaily, 27 January 2021.
[8] U.S. DEPARTMENT OF HEALTH AND HUMAN SERVICES National Institutes of Health NIH Publication No. 21-MH-8159 Revised 2021- Attention-Deficit/Hyperactivity Disorder in Children and Teens: What You Need to Know.
[9] Ville Karhunen, Tom A. Bond, Verena Zuber, Tuula Hurtig, Irma Moilanen, Marjo-Riitta Järvelin,Marina Evangelou, Alina Rodriguez."The link between attention deficit hyperactivity disorder (ADHD) symptoms and obesity-related traits: genetic and prenatal explanations."September 2021.
[10] Marlee M. Vandewouw, Kristina Safar, Sarah I. Mossad, Julie Lu, Jason P. Lerch, Evdokia Anagnostou & Margot J. Taylor."Do shapes have feelings? Social attribution in children with autism spectrum disorder and attention-deficit/hyperactivity disorder"September 2021.
[11] Thomas W. Frazier , Allison R. Frazier , Robyn M. Busch , Melissa A. Kerwood d, Heath A. Demaree."Detection of simulated ADHD and reading disorder using symptom validity measures"22 April 2008.

[12] Xiaolong Peng,Pan Lin ,Tongsheng Zhang,Jue Wang Published: November 19, 2013- Extreme Learning Machine-Based Classification of ADHD Using Brain Structural MRI Data
[13] Ville Karhunen, Tom A. Bond, Verena Zuber, Tuula Hurtig, Irma Moilanen, Marjo-Riitta Järvelin, Marina Evangelou & Alina Rodriguez Published: 04 September 2021-The link between attention deficit hyperactivity disorder (ADHD symptoms and obesity-related traits: genetic and prenatal explanations.
[14] Marlee M. Vandewouw, Kristina Safar, Sarah I. Mossad, Julie Lu, Jason P. Lerch, Evdokia Anagnostou & Margot J. Taylor Published: 25 September 2021-Do shapes have feelings? Social attribution in children with autism spectrum disorder and attention-deficit/hyperactivity disorder
[15] Bhaskar Sen,Neil C. Borle,Russell Greiner,Matthew R. G. Brown."The positive aspects of attention deficit hyperactivity disorder: a qualitative investigation of successful adults with ADHD"April 2018.



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