Attention deficit hyperactivity disorder detection using deep learning approach

Conference Paper · November 2023

DOI: 10.1109/ICCCNT56998.2023.10306955

Md Abrar Hamim
University of Wollongong

Alam Farzana
Daffodil International University

Orin Tasfia
Daffodil International University

Attention deficit hyperactivity disorder detection using deep learning approach.

Md Abrar Hamim
Department of Computer Science and Engineering
Daffodil International University
Dhaka, Bangladesh
abrar15-11821@diu.edu.bd

F.M. Tanmoy
Department of Computer Science and Engineering
Daffodil International University
Dhaka, Bangladesh
tanmoy15-13672@diu.edu.bd

Orin Tasfia
Department of Computer Science and Engineering
Daffodil International University
Dhaka, Bangladesh
orin15-13959@diu.edu.bd

Farzana Alam Juthi
Department of Computer Science and Engineering
Daffodil International University
Dhaka, Bangladesh
farzana15-14021@diu.edu.bd

***Abstract*— ADHD, a neurodevelopmental disorder characterized by hyperactivity, inattention, and impulsivity, has many detrimental impacts and is out of proportion to age. ADHD causes executive failure and emotional instability, which can lower academic performance. We propose a machine learning and artificial intelligence-driven approach to diagnose and early detect this disease and assist ADHD medicine. SVM, logistic regression, XGBoost, AdaBoost, and two deep learning models were applied to our dataset (ANN and CNN). Our ANN model had 99% accuracy in dependability, expandability, and generalizability. We plan to use our machine learning technology to enhance ADHD diagnosis and treatment for everyone.**

Keywords—ADHD,Machine-learning, ANN, Implementation, Diagnosis

I. Introduction

The most important details are the need for accurate diagnoses, inadequate development, and lack of attention disorder (ADH) as a major threat to the public's capacity to get accurate diagnoses. ADHD is defined by a pattern of chronic inattention and/or impulsive conduct that interferes with functioning or development. Symptoms of ADHD may occur between the ages of 3 and 6 and can include hyperactivity-impulsivity, poor academic achievement, workplace difficulties, and failing personal relationships. Significant correlations exist between the Stroop effect and the ADHD score and smartphone or tablet use. 18-24-year-old men had the greatest prevalence of ADHD and are more prone to use digital gadgets for over 6 hours each day. Treatment and treatment of ADHD should be prioritized to improve daily performance and reduce depression.

II. Current Diagnosis Methods of ADHD

The current comprehensive assessment for ADHD should include a comprehensive history of the patient's primary symptoms, a bio-psychosocial evaluation, medical records, and rating scales for ADHD behavior. Additionally, any family history of ADHD or co-occurring disorders should be recorded. Machine learning may be a better alternative to diagnosing and treating ADHD, as it can extract information from data that humans are unable to do. However, there is still bias to support the use of psychological and pharmacological interventions for treating primary ADHD symptoms. We proposed a solution to the most common treatment for ADHD in adults, psychostimulants, and used machine learning, deep learning, and deep neural networks to extract the optimal quantity of data and enhance it with data gathered in the future. We concluded that the new system can be implemented to better assist medical fields that deal with ADHD and to better diagnose the disease as early as possible.

III. Literature Review

Hybrid strategy of machine learning and expert knowledge models diagnose ADHD in adults with 95% accuracy, improving patients' health and well-being. [1]

Authors evaluate AI-based diagnostic tools for neurodevelopmental and behavioral disorders, highlighting challenges of traditional diagnosis methods, suggesting further research for more accurate diagnostic biomarkers for early detection of ASD and ADHD. [2]

Long-term video EEG data from children with ADHD may improve diagnosis and lead to more precise diagnostic tools and better treatment options by identifying the potential function of brain networks in the diagnostic process. [3]

Machine learning model using EEG data achieves 84% accuracy in identifying children with ADHD, showing potential for using changes in brain activity as a diagnostic tool, while also highlighting behavioral differences between children with ADHD and typically developing children. [4]

Light-GBM algorithm distinguishes control, ADHD, obesity, and pathological gambling participants with 80% accuracy, and CAARS-S tool holds promise for diagnosing adult ADHD and multiclassification of illnesses with ADHD-like symptoms in clinical settings. [5]

Pattern recognition used to differentiate between ADHD and control subjects through high- and low-frequency characteristics, and a machine-learning-based expert system built to evaluate ADHD therapy success, achieving an average accuracy of 0.999 with techniques such as Generalized Linear Model, Logistic Regression, Learning Techniques, and SVM classification.[6]

Supervised and nature-inspired computing methodologies review major psychological problems, presenting a roadmap for future research on psychiatric diagnoses, and the random forest achieves the highest prediction accuracy of 92.8%.[7]

83 ADD/ADHD affected youth and young adults undergo baseline evaluation, including rating scales, performance tests, MRI scans, and blood/urine measurement, with four machine learning techniques used, and support vector machine achieving 84.6% accuracy in forecasting methylphenidate response in an eight-week study. [8]

A study used support vector machine to classify ADHD individuals with 92% accuracy using non-linear techniques and suggested that ERP subcomponents can be used to define clinical groups based on unique features.[9]

The study reviews various diagnostic methods for ADHD using machine learning and deep learning, including MRI, EEG, HRV, questionnaires, CPT, RST, accelerometers, actigraphy, pupillometrics, genetics, social media, and AI, reporting an 87.2% accurate identification rate of ADHD patients.[10]

Individuals with ADHD, particularly those with alcohol or drug abuse problems and antisocial disorders, are at higher risk of developing substance use disorder. Mental comorbidities, mood, and anxiety issues also contribute to substance abuse problems, which can occur in younger people. [11].

ADHD is a behavioral illness with symptoms such as inattention, impulsivity, and hyperactivity that can last from infancy to adulthood, potentially caused by genetic and environmental factors, with a high prevalence rate in children; treatment options include flavonoids, omega-3 and omega-6 fatty acids, minerals, and B vitamins.[12]

ADHD is a disorder characterized by inattention, impulsivity, and hyperactivity, affecting 5-10% of children globally, with impairments in social and occupational functioning, and commonly treated with therapies based on reward processing, which may induce elevated systemic oxidative stress; new studies suggest potential correlation between ADHD and pollutants exposure and lack of green space. [13]

ADHD diagnosis and prescription sales are increasing globally, with the United States experiencing a rise in parental reports from 7.8% in 2003 to 11% in 2011 and then to 9.5% from 2011 to 2013.[14]

Children's ADHD rates may be linked to high levels of air pollution and lack of green spaces; ADHD is prevalent in 5-10% of kids and can lead to impairments in social, academic, and occupational functioning, and may be associated with oxidative stress.[15]

A study of 192 children with ADHD aged 8 to 16 found that exposure to digital media during the pandemic affected core symptoms of ADHD, emotional state, life events, learning motivation, EF, and family environment, and those who met a threshold on the Young's internet addiction test or the Self-Rating Questionnaire for Problematic Mobile Phone Use were classified as having ADHD with problematic digital media use. [16]

It discusses three-year research. 80% of studies passed. ADHD PRS, features, brain architecture, education, externalizing behavior, cognitive difficulties, physical health, and socioeconomic status were connected.[17]

The purpose of this review is to bring attention to recent research on autism spectrum disorder (ASD), attention deficit hyperactivity disorder (ADHD), and the comorbid condition (ASD+ADHD), drawing attention to shared symptoms, diagnostic challenges, and therapeutic options.[18]

A total of 366 individuals checked out the text and gave it their stamp of approval. The study of ADHD has been bolstered by a meta-analysis. These enable definitive statements on illnesses' characteristics, progressions, outcomes, causes, and therapies; hence, they help eliminate unnecessary stigma and misinformation.[19]

Thirty percent of the children with ADHD improved significantly over the follow-up period, whereas sixty percent relapsed after the first phase. At the conclusion of the study, only 9.1% of the original sample had fully recovered (maintained remission). [20]

Feature extraction for deep learning model training was achieved by multitaper and multivariate variational mode decomposition techniques. To classify ADHD, both the linear discriminant and the vector machine performed well. In 0.1 seconds, the methods had a sensitivity of 95.54 percent when identifying 1210 test samples.[21]

SNPs in SNAP25, DRD4, and ADGRL3 were studied to see whether they were associated with ADHD symptoms in Caribbean families.[22]

A reduced-order model is created using Galperin fuzzification and the Euler-Lagrange principle. Galperin's approach is used to calculate the van der Pol wake oscillation coefficients using a five-mode approximation.[23]

Children with ADHD were split evenly between the hyperactive and non-hyperactive categories, with 50% each. Usability evaluations were also obtained, along with an overall diagnostic efficiency of 0.89 (sensitivity = 0.93, specificity = 0.86).[24]

The study's overarching purpose is to establish a machine learning-based strategy to categorizing kids as either healthy or impacted by ADHD by identifying the most important risk factors for the disorder in kids.accuracy in classification of 85.5%, specificity of 86.4%, and sensitivity of 84.4% were all attained by the RF-based classifier, as reported by the study. [25]

IV. METHODOLOGY

In this article, we will discuss how all of the procedures involved in putting all of the techniques into action were actually carried out. During the development process, the processes are used to design, develop, and implement new techniques and modify existing ones. Throughout the development process, each step and procedure are beneficial.

Here in Fig 1. The whole Methodology process is visualized in a concise manner, We will Describe the whole process according to the diagram.

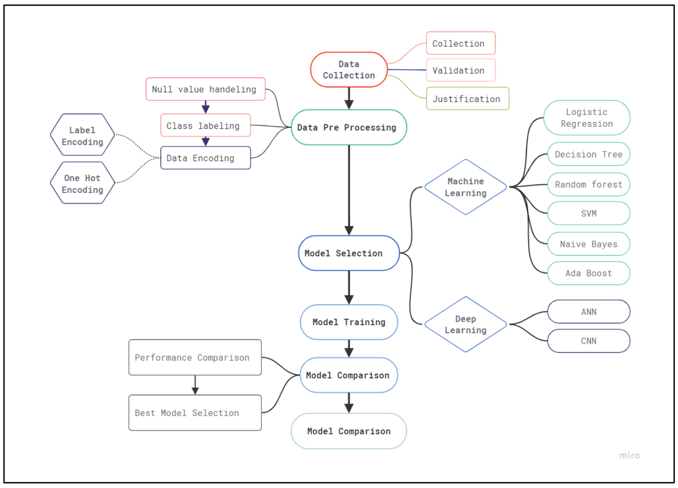

Fig. 1. Methodology for the research process.

A. *Data Collection*

Data gathering techniques were created and interviewed with project doctors and senior supervisors. Age groups were 25–30; 40–50; and 60–65. Data collection forms were produced and circulated. To grasp the issue, Google Form created dynamic questions. Data was stored with a partner in CSV format. After asking, findings were found in processes like source, collection approach, approval, realness, and avocation of inquiries.

B. *Data preprocessing*

Data preparation is the process of cleaning, categorizing and analyzing data from field surveys and other sources using a variety of tools and methods. Manual inspection is the initial step of any data preparation procedure, which includes the human assessment of missing values, data swapping issues, and incorrectly named features. There are no use of artificial intelligence or machine learning in this process, and the datasets we employ for algorithms have the potential to give birth to a wide variety of challenges:

a. *Null value handling*:

Several datasets have missing values. Missing data can affect machine learning algorithms and model accuracy. Python and Sklean helped us handle missing values in our dataset. We imputed missing data using basic techniques. This method was chosen since our dataset only contains categorical "Yes" and "No" values. Hence, the most common filling approach maximizes imputation.

b. *Data Class identification*:

Analyzing data classifies it. This human technique requires no identifying algorithm or machine learning. First, the necessity. All databases are not labeled. Machine learning uses two data kinds. labeled and not. Simple labels divide the data into two or more groups. Since we can't tell which data points belong to which class, unlabeled data can be difficult. So, the initial step is classifying each dataset row. For medical datasets, we must visit a licensed physician to validate classifications, etc. Our focus is the ADHD dataset. Information is collected using ADHD-symptom questionnaires. We meticulously identified and labeled all data. Data class assignment complete.

c. Data type: inspection and encoding

Data preparation encoding is crucial. It is not optional, although not all datasets require it. Machine learning encoding has two main types. label and one-hot encoding.

Encoding represents. largely a string or object-type dataset that represents category data in numeric form. mostly numbers.

Label encoding makes labels machine-readable. Machine learning algorithms may then identify the best labeling strategy. Preprocessing structured data for supervised learning is essential. Our dataset's questions have "yes" or "no" answers. Computers cannot calculate "yes" and "no" since they are strings. Label encoding will encode "yes" and "no" as 1 and 0, respectively. This tells the machine to interpret these words. We instruct the computer "yes" and "no."

Another important encoding component follows. Category labels are numbers, as indicated above. Hence, if there are more than two categories, would the models not show one category as better and the data not be ordinal, despite our wishes?

Since our ADHD dataset is merely "yes" and "no," we don't need to execute one hot encoding to remove any ordinal nature.

C. *Model Selection and implementation*

Machine learning and deep learning are two models used to analyze data. Deep learning models are used more for visual computer vision and higher-dimensional data than machine learning models for statistical data. Logistic regression, also known as logit regression, is a type of regression analysis used to calculate an outcome's likelihood in light of a variety of variables. The sigmoidal curve is used by the model to determine the probability of the event occurring. Formulas for the parabolic curve in its mathematical form include:

$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}}$$

Here xo is the x value of the sigmoid mid-point
L, the supremum of the values of the function;
K, the logistic growth rate or steepness of the curve
And here is the Sigmoid curve function

$$s(x) = \frac{1}{1 + e^{-x}} = \frac{e^x}{e^x + 1} = 1 - s(-x)$$

SVM solves categorization problems using machine learning. Supervised learning regression and classification problems use it most. SVM finds the optimal line that divides n-dimensional space into classes to classify subsequent data points. The sigmoid curve calculates and divides ADHD risk into two classes, but the results seem too perfect. To feed the network a vector of input feature data and compute a one-dimensional vector of labels, a linear kernel with a gamma value of 0.7 is preferred. SVM selects hyperplane vectors, hence its name. All SLVM, hyper plane, and support vector formulas are calculated.
Hyperplane equation can be easily written as:

$$H: w^T(x) + b = 0$$

b = Bias term and intercept of the hyperplane equation
The hyperplane would always be D -1 operator in In D dimensional space.

For instance, a hyperplane is a straight line (1-D) for 2-D space.
The distance of a hyperplane from any point:

$$d_H(\phi(x_0)) = \frac{|\omega^T(\phi(x_0)) + b|}{\|\omega\|_2}$$

Here ||w||2 is the Euclidean norm for the length of w given by:

$$\|w\|_2 =: \sqrt{\omega_1^2 + w_2^2 + \omega_3^2 + \cdots + w_n^2}$$

Naive Bayes:
Simple, effective Naive Bayes categorization. For millions of records with properties, use Naive Bayes. Naive Bayes performs well with textual data. Machine learning and statistics Our data is unique. The Naive Bayes classifier (NB) is a simple and effective way to learn from data without knowing the attribute distribution. maximize that.
Bayesian theorem regulates Naïve Bayes classification logic:

$$P(H|E) = \frac{P(E|H) * P(H)}{P(E)}$$

Here :
P(E|H) : Likelihood that the evidence supports the hypothesis
P(H|E) : posterior probability
P(E) : prior probability of the evidence is true
P(H) : probability of hypothesis
As for the implementation details, we used the base classifier.
Decision Tree and Random Forest:
Decision tree and Random Forest are functionally identical, however only decision tree is user-friendly and computationally costly. Others argue that a random forest is one type of decision tree and may be better. You decide. Decision tree and random forest accuracy are 95% and 96%. Decision trees have a 13-depth limit, while random forests have 7. The impurity measure—the decision criterion for dividing and categorizing—is the most crucial aspect of any decision tree.
For example, the GINI impurity formula is:

$$GINI = 1 - \sum_{i=1}^{C} \blacksquare (P_i)^2$$

These are the models that form the basis of our machine learning analysis. There are other external, independently developed algorithms that are used to classify our dataset. they are :
Ada-Boost :
A machine learning technique utilized in the ensemble method is called AdaBoost, sometimes named "adaptive boosting." Decision trees with a single split or one-level decision trees, are the approach that the users choose to utilize with AdaBoost. "Decision stumps" are another name for them. A big shortcoming of AdaBoost is that it has no mechanism for selecting the best features to use in making predictions. However, since our dataset is so restricted and regulated, we do not need it with 100 estimators.
Deep learning algorithms:
Due to their ability to mimic human learning, deep learning algorithms provide a more accurate and efficient means of categorization. Although we largely used the fundamental ANN and CNN methodologies, these neural networks are really far more involved than they first seem to be. More effectively, we used CNN and ANN for our particular ADHD dataset.
ANN:
The artificial neural network (ANN) is the first method for deep learning. For us this method has a total of eight layers. Our dataset as well as the symptoms are associated with it are contained in the input layer, which is the topmost layer.
CNN:
The convolutional neural network (CNN) is the second method, and it is made up of both convolutional and recurrent layers. In order to properly create our layers, we started with a three-convolutional layer, then moved on to a batch normalization layer, and then finished with a max pooling and flattening layer. For the purpose of probability extraction, SoftMax activation is being used here

D. Model buildign and training

Machine learning models yield promising results, so we may use them to classify our dataset. We have taken all required steps to fine-tune our models to fit our dataset and get the most accurate results. The algorithms learn to divide ADHD symptoms into two categories. This use scenario prevents regression model use. Classification models are customized.

E. Model Comparison and Best model selection

The most significant facts of ANN, CNN, SVM, accuracy, and validation are that machine learning models with 100% to 99% accuracy are overfitted, and ANN and CNN models are DNN subtypes (deep neural networks). Accuracy matrices and prediction arrays can determine data bias and the optimum model. The ANN model is more accurate and reliable and may be used to train and assess performances throughout graph-view epochs.
For this one we are using ANN First

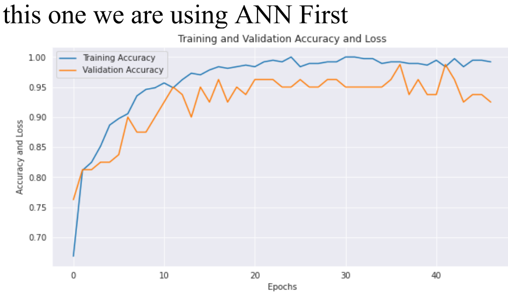

Fig 2. Training Accuracy and Validation Accuracy of ANN respect to epochs.

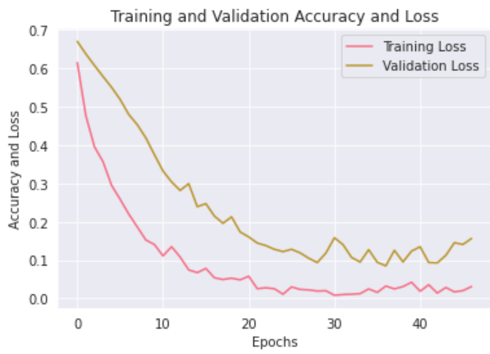

Fig 3. Training loss and validation loss of ANN

Now for the validation and training performance of the CNN model:

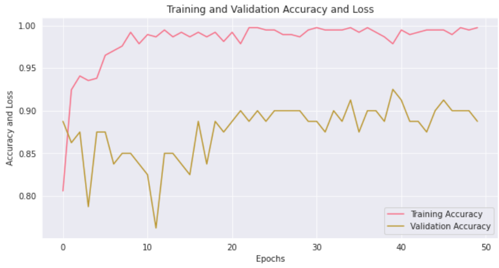

Fig 4. Training and Validation Accuracy of CNN respect to epochs

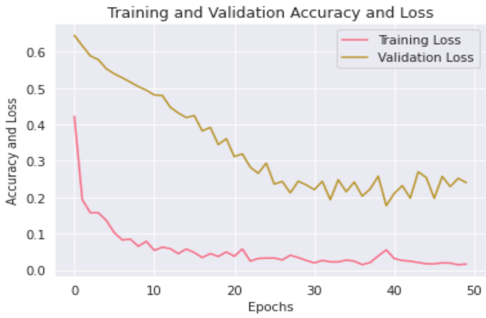

FIGURE 5. TRAINING LOSS AND VALIDATION LOSS OF CNN

V. RESULT ANALYSIS

The purpose of this work is to determine which machine learning or deep learning algorithm is the most effective for predicting ADHD symptoms. The open-source Scikit-Learn library of machine learning models was used, which integrates the functionality of NumPy, SciPy, matplotlib, and I Python Notebook into a single software tool. Accuracy is a measure of how well an algorithm can classify people with and without ADHD, and a range of accuracy is considered acceptable. The majority of algorithms obtain an accuracy between 95% and 98%, with the ANN model achieving the best accuracy, followed by the CNN algorithm and the Decision tree. The SVM and logistic regression is omitted. As it is visualized in fig 2 and 3

The two accuracies of the deep learning models are also discussed. The question may arise that why deep learning approaches rather than machine learning are chosen:

Table 1. Comparison of Deep learning models

Model	Accuracy
ANN	99.%
CNN	97.44%

This here, Table 1 shows that the ANN model is much more effective for finding the possibility of ADHD rather than CNN. These models are not more than machine learning models in any sense. For example, the second table below shows that the most effective model of machine learning models is :

Table 2. Comparison of best machine learning models.

Model	Accuracy
svm	100%
Logistic Regression	99.67%

Here in Table 2 the Comparison of the machine learning models are shown, From assessing the Data from this table, We came to the realization that the SVM and Log-Reg models of machine learning are more likely to be overfit than the deep learning models. This is the conclusion that we came to. We anticipate that the deep learning models will provide findings that are more generic than those produced by machine learning models.

This is also to be anticipated from a clinical view, taking into consideration a significant amount of information that is both pertinent and targeted is now incorporated into the training through utilizing risk assessment, which is performed explicitly as a clinical activity. Because it is such a common method, there is a significant possibility of adverse effects occurring in a therapeutic setting when it is used.

Table 3. Performance measure of all models.

Model	Accuracy
SVM	100%
ANN	99.19%
CNN	98.9%
Logistic regression	97.17%
Decision tree	95.7%
Random Forest	95.2%
Naïve Bayes	94.0%

The most important details to notice In Table 3 is about the accuracy of both ANN and CNN models are the model loss and accuracy. Model loss That is visualized in Fig 3 and 5 respectively, is a concept that requires the selection of a loss function during model design and configuration to assess a potential solution in the context of an optimization technique. Model accuracy is a measure that represents the performance of a model across all classes and is estimated by dividing the total number of possibilities by the proportion of accurate forecasts. Implementation of ANN on our dataset yielded a model loss of 0.02 at the end of 25 epochs and a model accuracy of 99.99 percent, while the validation accuracy was 0.98 or 98% respectively. At the conclusion of 52 epochs, our implementation of the CNN model produces a model loss of 0.,0.02, while simultaneously achieving a model accuracy of $98, or 98%.

VI. CONCLUSION & FUTURE WORKS

To improve ADHD diagnosis, we're using AI. Machine learning and deep learning train models to predict ADHD based on symptoms. This technique reduces waiting lines, accelerates diagnosis, and expedites treatment. This strategy improves ability, transferability, adaptability, and precision based on machine learning method. An Android app with an AI algorithm is the main goal.

This includes creating a form system with artificial intelligence model questions to diagnose ADHD. Knowing what percentage of problems can be solved automatically and what percentage require human intervention makes the AI system more successful. Yet, an AI system will diagnose easy situations, while more experienced clinicians will handle difficult cases.

VII. References

[1] Tachmazidis, Ilias, Tianhua Chen, Marios Adamou, and Grigoris Antoniou. "A hybrid AI approach for supporting clinical diagnosis of attention deficit hyperactivity disorder (ADHD) in adults." Health Information Science and Systems 9, no. 1 (2021): 1-8.

[2] Mengi, Mehak, and Deepti Malhotra. "Artificial Intelligence Based Techniques for the Detection of Socio-Behavioral Disorders: A Systematic Review." Archives of Computational Methods in Engineering (2021): 1-45.

[3] Zhou, Dingfu, Zhihang Liao, and Rong Chen. "Deep Learning Enabled Diagnosis of Children's ADHD Based on the Big Data of Video Screen Long-Range EEG." Journal of Healthcare Engineering 2022 (2022).

[4] Parashar, Anshu, Nidhi Kalra, Jaskirat Singh, and Raman Kumar Goyal. "Machine learning based framework for classification of children with adhd and healthy controls." INTELLIGENT AUTOMATION AND SOFT COMPUTING 28, no. 3 (2021): 669-682.

[5] Christiansen, Hanna, Mira-Lynn Chavanon, Oliver Hirsch, Martin H. Schmidt, Christian Meyer, Astrid Müller, Hans-Juergen Rumpf, Ilya Grigorev, and Alexander Hoffmann. "Use of machine learning to classify adult ADHD and other conditions based on the Conners' Adult ADHD Rating Scales." Scientific reports 10, no. 1 (2020): 1-10.

[6] Loh, Hui Wen, Chui Ping Ooi, Prabal Datta Barua, Elizabeth E. Palmer, Filippo Molinari, and URajendra Acharya. "Automated detection of ADHD: Current trends and future perspective." Computers in Biology and Medicine (2022): 105525.

[7] Ghasemi, Elham, Mansour Ebrahimi, and Esmaeil Ebrahimie. "Machine learning models effectively distinguish attention-deficit/hyperactivity disorder using event-related potentials." Cognitive Neurodynamics (2022): 1-15.

[8] Kaur, Prableen, and Manik Sharma. "Diagnosis of human psychological disorders using supervised learning and nature-inspired computing techniques: a meta-analysis." Journal of medical systems 43, no. 7 (2019): 1-30.

[9] Mueller, Andreas, Gian Candrian, Juri D. Kropotov, Valery A. Ponomarev, and Gian-Marco Baschera. "Classification of ADHD patients on the basis of independent ERP components using a machine learning system." In Nonlinear biomedical physics, vol. 4, no. 1, pp. 1-12. BioMed Central, 2010.

[10] Kim, Jae-Won, Vinod Sharma, and Neal D. Ryan. "Predicting methylphenidate response in ADHD using machine learning approaches." International Journal of Neuropsychopharmacology 18, no. 11 (2015).

[11] Biederman, Joseph, Timothy Wilens, Eric Mick, Sharon Milberger, Thomas J. Spencer, and Stephen V. Faraone. "Psychoactive substance use disorders in adults with attention deficit hyperactivity disorder (ADHD): effects of ADHD and psychiatric comorbidity." (1995).

[12] Kidd, Parris M. "Attention deficit/hyperactivity disorder (ADHD) in children: rationale for its integrative management." Alternative Medicine Review 5, no. 5 (2000): 402-428.

[13] Van Hulst, Branko M., Patrick De Zeeuw, Dienke J. Bos, Yvonne Rijks, Sebastiaan FW Neggers, and Sarah Durston. "Children with ADHD symptoms show decreased activity in ventral striatum during the anticipation of reward, irrespective of ADHD diagnosis." Journal of Child Psychology and Psychiatry 58, no. 2 (2017): 206-214.

[14] Davidovitch, Michael, Gideon Koren, Naama Fund, Maayan Shrem, and Avi Porath. "Challenges in defining the rates of ADHD diagnosis and treatment: trends over the last decade." BMC pediatrics 17, no. 1 (2017): 1-9.

[15] Yuchi, Weiran, Michael Brauer, Agatha Czekajlo, Hugh W. Davies, Zoë Davis, Martin Guhn, Ingrid Jarvis et al. "Neighborhood environmental exposures and incidence of attention deficit/hyperactivity disorder: A population-based cohort study." Environment International 161 (2022): 107120.

[16] Shuai, Lan, Shan He, Hong Zheng, Zhouye Wang, Meihui Qiu, Weiping Xia, Xuan Cao, Lu Lu, and Jinsong Zhang. "Influences of digital media use on children and adolescents with ADHD during COVID-19 pandemic." Globalization and Health 17, no. 1 (2021): 1-9.

[17] Ronald, Angelica, Nora de Bode, and Tinca JC Polderman. "Systematic review: how the attention-deficit/hyperactivity disorder polygenic risk score adds to our understanding of ADHD and associated traits." Journal of the American Academy of Child & Adolescent Psychiatry 60, no. 10 (2021): 1234-1277.

[18] Antshel, Kevin M., and Natalie Russo. "Autism spectrum disorders and ADHD: Overlapping phenomenology, diagnostic issues, and treatment considerations." Current psychiatry reports 21, no. 5 (2019): 1-11.

[19] Faraone, Stephen V., Tobias Banaschewski, David Coghill, Yi Zheng, Joseph Biederman, Mark A. Bellgrove, Jeffrey H. Newcorn et al. "The world federation of ADHD international consensus statement: 208 evidence-based conclusions about the disorder." Neuroscience & Biobehavioral Reviews 128 (2021): 789-818.

[20] Sibley, Margaret H., L. Eugene Arnold, James M. Swanson, Lily T. Hechtman, Traci M. Kennedy, Elizabeth Owens, Brooke SG Molina et al. "Variable patterns of remission from ADHD in the multimodal treatment study of ADHD." American Journal of Psychiatry 179, no. 2 (2022): 142-151.

[21] KASIM, Ömer. "Identification of Attention Deficit Hyperactivity Disorder with Deep Learning Model." (2022).

[22] Cervantes-Henríquez, Martha L., Johan E. Acosta-López, Ariel F. Martinez, Mauricio Arcos-Burgos, Pedro J. Puentes-Rozo, and Jorge I. Vélez. "Machine learning prediction of ADHD severity: association and linkage to ADGRL3, DRD4, and SNAP25." Journal of Attention Disorders 26, no. 4 (2022): 587-605.

[23] Dai, Huliang, Abdessattar Abdelkefi, Qiao Ni, and Lin Wang. "Modeling and identification of circular cylinder-based piezoaeroelastic energy harvesters." Energy Procedia 61 (2014): 2818-2821.

[24] Lindhiem, Oliver, Mayank Goel, Sam Shaaban, Kristie J. Mak, Prerna Chikersal, Jamie Feldman, and Jordan L. Harris. "Objective Measurement of Hyperactivity Using Mobile Sensing and Machine Learning: Pilot Study." JMIR Formative Research 6, no. 4 (2022): e35803.

[25] Maniruzzaman, Md, Jungpil Shin, and Md Al Mehedi Hasan. "Predicting Children with ADHD Using Behavioral

Activity: A Machine Learning Analysis." Applied Sciences 12, no. 5 (2022): 2737.