INTERNATIONAL JOURNAL OF
Telecommunications
AIR DEFENSE COLLEGE

Review Study on Artificial Intelligence Tools for Attention Deficit Hyperactivity Disorder Identification

Eman Salah [1,*], Mona Shokair[2], Fathi Abd El-Samie[3] and Wafaa A. Shalaby[4]

[1]HIGH INSTITUTE FOR ENGINEERING AND TECHNOLOGY AL-OBOUR; eman.salah090@gmail.com.
[2] Communications Department, Faculty of Electronic Engineering, mona.sabry@el-eng.menofia.com.
[3]**Communications Department, Faculty of Electronic Engineering, fathi_sayed@yahoo.com.**
[4]**Communications Department, Faculty of Electronic Engineering, engwafaaahmed88@yahoo.com.**

Citation:
Salah, E.; Shokair, M.; Fathi, A. El-Samie; Wafaa, A .
*Inter. Jour. of Telecommunications, IJT'*2023,
Vol. 03, Issue 01, pp. 1-12, 2023.
Editor-in-Chief: Youssef Fayed.
Received: 16/03/2023.
Accepted: date 04/05/2023.
Published: date 08/05/2023.

Abstract: Attention deficit hyperactivity disorder (ADHD) is the most common developmental disease in childhood and adolescence. Most similar previous ADHD classification studies have only classified ADHD and normal categories. This study was the first attempt to classify adults with ADHD by means of a support vector machine indicating that classification by nonlinear methods is possible in the context of clinical populations. Some of the guidelines were used in this systematic review to analyze the studies most relevant to the diagnosis of ADHD using the Deep learning (DL) approach. This paper also attempted to look at the process of ADHD development; what are the associated problems? And how many other children and adults are affected by such problems around the world the basis for understanding ADHD more accurately in order to develop a better multi-modal medical and/or non-medical intervention plan and some classification technique of ADHD will be presented. The diagnosis of it includes conducting some psychological tests, but it may not give accurate results, so the diagnosis is made using non-invasive imaging, which is called Magnetic Resonance Imaging (MRI). For this purpose and according to the medical imaging system, first, the images are pre-processed, and then 3D images are taken and this is done using the ADHD-200 training data set. This shows the best results and classification with high accuracy.

Keywords—ADHD, deep learning, fMRI, CNN, Feature extraction.

1. Introduction

Recently, some machines can be used to make a comparison between artificial intelligence and human intelligence, and these machines are like computers. It is known that the person is infected through his emotional behavior and that he often does not settle for a certain job, and his relationship with people is always abnormal. Through machine learning, patterns are recognized in all fields [1-2]. This disease is very famous and widespread in the United States of America [3].

So much so that every child out of 10 children between the ages of 5 and 17 suffers from ADHD. This disorder affects 5-10% of children and has lifelong impairment. The incidence of ADHD continues to rise and may extend into adolescence and adulthood due to a lack of appropriate medications [4]. It is also possible that the symptoms of hyperactivity are impulsivity and curiosity, as children who are not attentive and impulsive have severe difficulty concentrating and acting impulsively without looking at the consequences of this impulsivity [5]. This results in a high risk of developing symptoms and behaviors of this disorder, in addition to the lack of appropriate treatment, such as obsessive-compulsive disorder and the risk to pregnant women as a result of lack of nutrition and alcohol consumption, which affects the neurodevelopment of children and also faces difficulty related to learning [6]. Recent research also showed the presence of abnormalities in different brain regions [7-8].

Functional Magnetic Resonance Imaging (FMRI) is used in data analysis. Where the lack of specific techniques for diagnosing ADHD has stimulated research to accurately identify ADHD using data [9]. The classification of ADHD depends on the electroencephalogram (EEG) [10-11]. This study is concerned with the diagnosis of ADHD using FMRI data. There are many disorders or diseases that can be treated and identified using deep learning like Cancers, Hearing, Arthritis, Feelings of Nervousness or Restlessness, and chronic symptoms.

Persons with this problem suffer by reducing self-confidence has a role to play in depression people diagnosed with ADHD tend to pursue the disorder when it reaches the stage of puberty [12]. Also, there are many studies that have proven that there are a lot of mental illnesses that people suffer from over the years now [13-14]. Often symptoms are identified at school because these children have a very difficult time succeeding in a classroom environment and teachers do not have the ability to diagnose the condition, but they may expect the presence of the disease and these symptoms include three things:

- Inattention
- Hyperactivity
- Impulsivity

This disease is associated with DMN in tasks that require engaging effort [15]. Similarity has shown difficulties suppressing defaults to scale people’s efforts with ADHD Challenges.

The remaining parts of this paper are organized as follows: Data and Statistics about ADHD will be displayed in Section 2, deep Learning will be explained in Section 3, the main structure of the system framework will be described in Section 4, classification Stages for ADHD will be introduced in section 5 and discussions will be made in Section 6 Finally, conclusions will be done in Section 7.

2. Data and Statistics about ADHD

The percentage of children with ADHD has changed over time and its measurement can change as well. The first survey was completed in 1997. Since that time, there has been an upward trend in the estimation of ADHD diagnoses reported by parents across different surveys, using different age ranges. It is not difficult to see if this increase represents a change in the number of children diagnosed. Symptoms persist, can be severe, and can cause difficulty at school, at home, or with friends. Good treatment plans will include close monitoring and follow-up and making changes, if necessary, along the way. The percentage of kids with this illness increases with age. Surveys show that 2.4% (388,000) of their age 2 to 5, and 9.6% (2.4 million) of these are from 6 to 11 years old have been diagnosed with this disorder. The rate of spending on affected children is 5 times the rate of spending on unaffected children [16]. Roughly 41% of families with children affected by this disorder also have parents affected [17-18]. Figure 1. NHIS (National Health Interview Survey) shows the annual report for statistics of infected children.

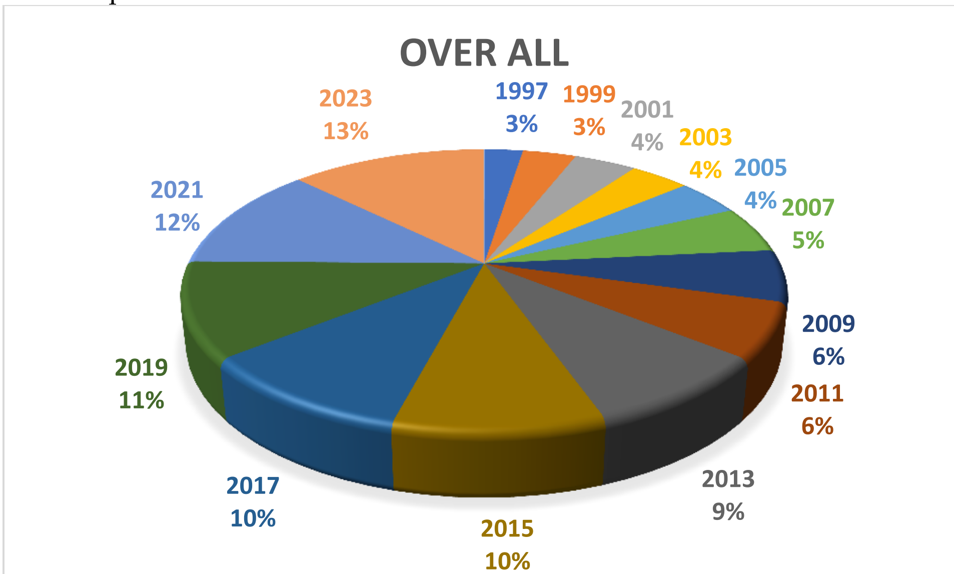

Figure 1. Annual statistics of infected children.

Figure 2 shows adults in excellent or very good health in 2012, it was about 79% like the previous year. Figures 3 and 4 show data from 2015 and 2018 and (NHIS) was used for this analysis. Figure5. Shows that there is also a yearly difference between boys and girls with ADHD. Also, research has been conducted on people with ADHD in Spain, where the degree of infection varies between people who hold Spanish nationality, non-Spanish children with white skin, and also the non-Spanish black person, Figure 6. Represents the Appearance by race/ethnicity as it follows:

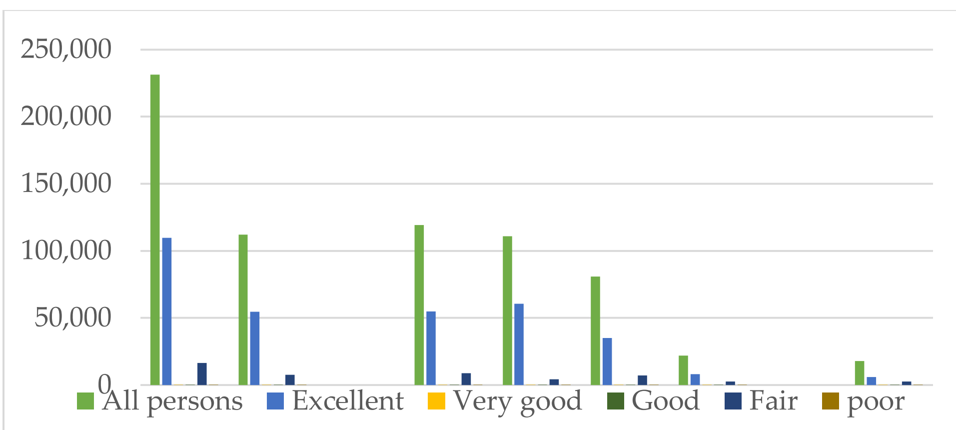

Figure 2. Distribution of the age-corrected percentage (with standard errors) of health status assessed by respondents, by selected characteristics: United States, 2012.

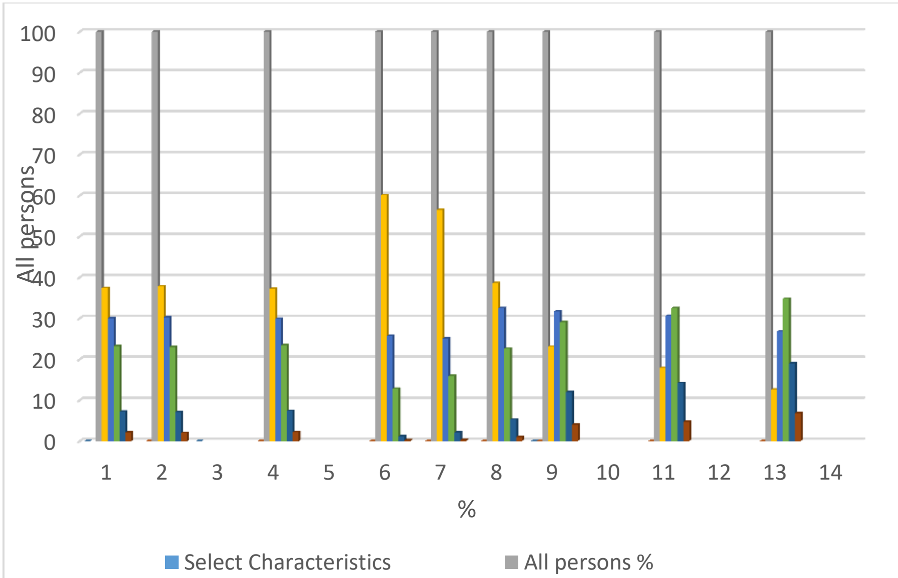

Figure 3. Distribution of the age-corrected percentage (with standard errors) of health status assessed by respondents, by selected characteristics: United States, 2015.

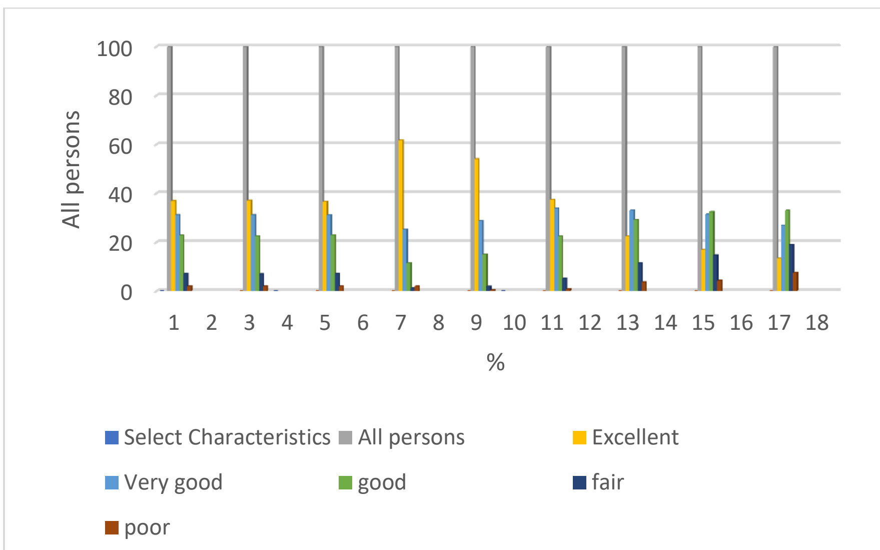

Figure 4. Distribution of the age-corrected percentage (with standard errors) of health status assessed by respondents, by selected characteristics: United States, 2018.

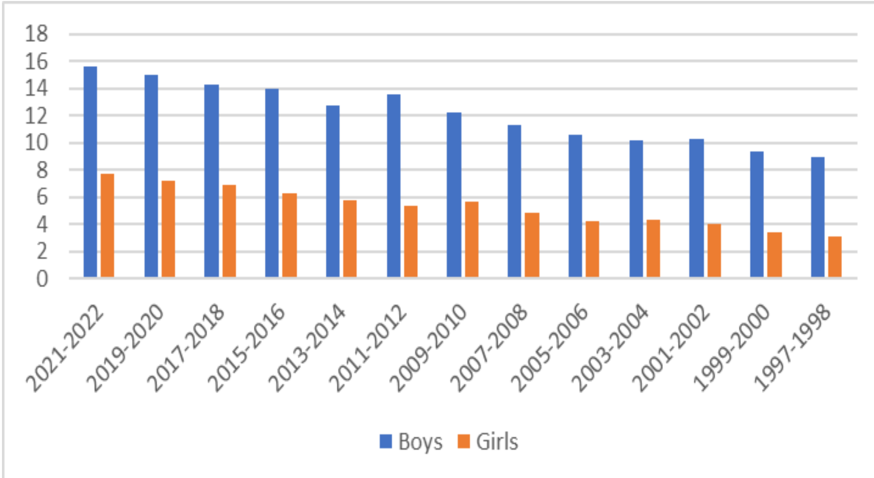

Figure 5. Spread by gender.

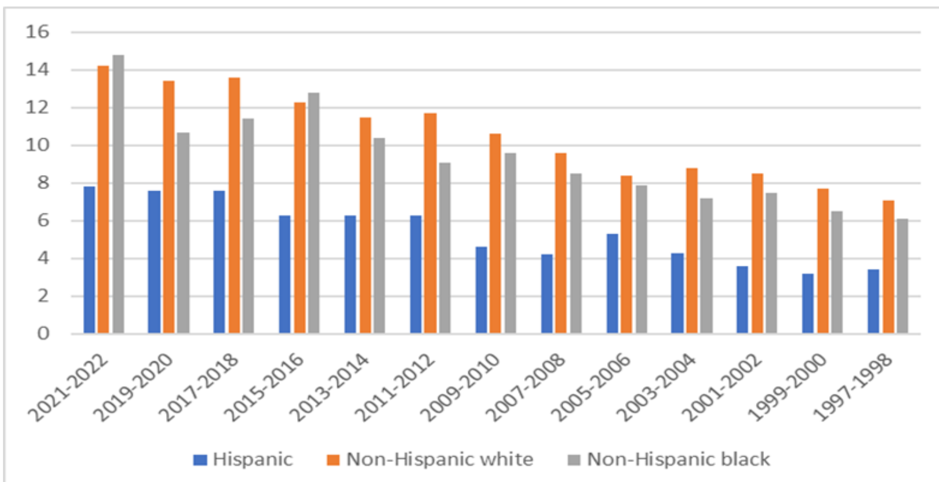

Figure 6. Appearance by race/ ethnicity.

Estimates of the prevalence of ADHD in adults vary in the United States. A 2019 study estimated this disorder in adults at 96%. The United States has determined the prevalence rate among adults at rates ranging between 2.5 and 4.4%.
And the data set until 2020 issued by the NCHS presented annual rates of increase in the incidence of these diseases, and it indicated that it has continued to increase until now.

3. Deep Learning

ML is an essential part of AI that makes computers able to learn without the need to program them [19]. And also, Dl has the ability to deal with medical images and is used in the processing and analyzing of a lot of things, and it will be used in many fields in the future [20-21]. To improve image processing and analysis using MRI, many methods of deep learning have been discovered

3.1. Convolution Neural Network (CNN)

It is used in a lot of research and modern projects [22]. And it has proven its effectiveness in various fields such as image recognition and classification, face recognition, traffic signals and objects, and it has the ability to analyze or classify linguistic sentences. A classification is made for this pathogen using CNN to extract its specifications [23-24]. Bypass neural networks or (CNN) include two nuclei Layers, which are bypassed and collected as Follows:

- Convolution layer [25].
- Pooling Layer [26].

In general, there are different types of CNN architectures, such as LeNet- 5[27], Alex Net [28], and ZFNet [29]. There are other types of CNN, such as the foundation and follow-up versions [30-31].

3.2. Pre-trained Models in Deep Learning

NNs are a different series of models than ML, and there are many reasons for this, the most famous of which is the cost of running the algorithms on the machine .The pre-trained model may not be very accurate, but it saves a lot of effort to produce a good model [32-33]. It can be used for extracted features. In this section, recent progress in applying embedded deep learning in image detection [34], image registration [35], image segmentation [36], and MRI image classification [37].

4. System Design

ADHD identification mode was designed with (FMRI) data known as ADHD-care V1 and illustrated in Figure 7. Where FMRI data was used, pre-processed, and then the features are extracted and selected from the pre-made data set. The CNN syntax has been developed efficiently, which leads to improved learning ability [38]. The neural network was built with a convolution layer of 32 filters with a kernel size of 3 * 3 with the activation function 'Relu'. The second layer was created by 64 candidates with the same specifications as the first layer. Then a pooling layer was added with a maximum pool size of 2 * 2. Added softmax activation function to enable classification.

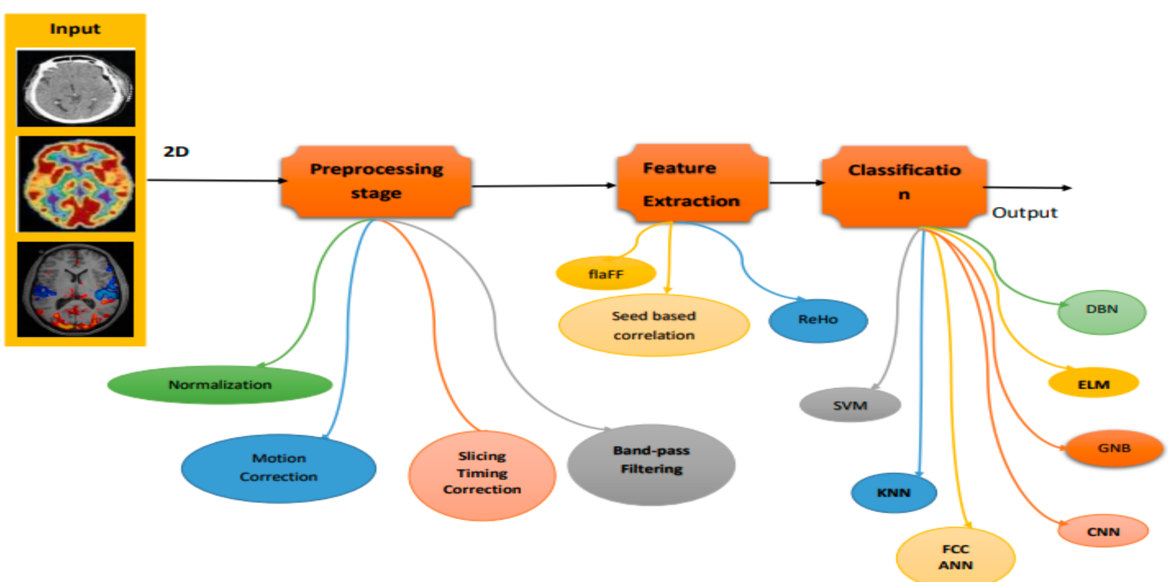

Figure 7. System Design.

4.1. FMRI Data

MRI is a modern imaging method and is used to determine brain. Which is based on radio waves and magnetic fields and produces detailed images of the various organs and issues of the body [39]. MRI takes a three-dimensional image of the body's organs and looks like a large tube or cylinder with a table in the middle on which the patient rests. FMRI is a special type of magnetic resonance that is used to measure the activity of different areas of the brain by measuring changes in the area in which blood is pumped [40].

4.2. Preprocessing Stage for FMRI

Preprocessing has the task of canceling unwanted artifacts and converting the data into a proprietary format. There are several widely used it. This technology can also be used for other electrical devices. While connecting lines, stepped impedance resonators and open-ended strings are used to design the bandpass channel.

4.3. Feature Extraction

Feature extraction aims to reduce the number of features in a data set by creating new features from existing features (and then discarding the original features). Analysis with a large number of variables generally requires a lot of memory and computational power and may cause the classification algorithm to be overloaded with training samples and generalize poorly to new samples. It is a general term for methods of creating groups of variables to get around these problems while still describing the data with sufficient precision. Many machine learning practitioners believe that properly optimized feature extraction is the key to building an efficient model [41].

5. Classification Stages for ADHD

There are also some classification techniques used to identify ADHD such as, Support Vector Machine (SVM), k-nearest neighbor's algorithm (KNN), CNN, face-centered cubic family Artificial Neural Network (FCC ANN), Gaussian Naive Bayes (GNB), Extreme Learning Machine (ELM), and Deep Belief Network (DBN). SVM maps training examples to points in space to increase the width of the gap between the two classes [42]. KNN is a type of classification where the function is only locally approximated and all arithmetic operations are deferred until the function is evaluated. CNN is a deep learning neural network designed to process structured arrays of data such as images. They are widely used in computer vision and have become a state-of-the-art technology for many visual applications such as image classification, and have also had success in natural language processing for text classification.

6. Discussion

Many of the statistics for ADHD depend on the study of classifications and there are different types of algorithms that you can use depending on the data set you are working with. The most common algorithm SVMs in machine learning are; Logistic Regression, Naïve Bayes, k-nearest neighbors, Decision Trees, and SVM. Where Logistic regression is a mathematical method by which a binary outcome is predicted, meaning either something will happen or not, right or wrong, and so on, Naive Bayes calculates whether or not a data point belongs to a particular class, KNN is a pattern recognition algorithm that uses training datasets to, A decision tree is a supervised learning algorithm that is ideal for classification problems, as it is able to rank classes at a specific level, SVM uses algorithms to train and classify data and is the best type because it is the most accurate and multi-dimensional. The SVM/LDA classifier can also be considered as a generalization of Linear Differentiation Analysis (LDA) by incorporating the idea of (local) margin maximization into the standard LDA formulation

Recently, many CNNs have been proposed not only for 2D images but also for 3D and 4D volume segmentation. However, due to the large data size of the latter, it is more difficult to obtain a sufficient amount of annotations for training than it is for 2D images. X-ray, computed tomography (CT), (MRI), and electron microscopy (EM) are some of the methods that have been used to collect 3D information, These methods are becoming progressively faster, and this has helped collect volumes that form 3D movies of temporal events or 4D datasets.

Artificial intelligence is expected to contribute to all major advancements and is likely to be a helping hand in all industries. We have discussed some of the most used tools in AI in recent years. Other AI tools are getting more and more popular like Google ML kit, Theano, Swift AI, Deeplearning4j, etc. These AI technologies can fuel advances in this field and have the potential to improve human effort in every possible area of real-life AI applications.

Increasing evidence indicates that patients with ADHD suffer from cognitive impairment and social problems, and the most worrying thing about this disease is the difficulty of dealing with others, and this poses a great danger. Many attempts have been made in order to discover the appropriate psychological treatment. Our main goal was how to identify this disease through their behavior or facial expressions or emotions. Children and teens with ADHD have some disabilities and are less able to identify emotions. There are many studies on the ability to recognize emotions from the faces of these children. Those who have this type of disorder have a delay in brain development and cognitive ability is weak, and adolescents with ADHD always have a difficult period because of emotions. In light of this information, these delays in brain maturation observed in ADHD may lead to impairments in recognizing faces such as emotions to identify them. It may lead to a personality disorder and severe weakness in social behavior and emotional relationships. Some developments have been made in the analysis of magnetic resonance imaging (MRI) methods in order to enable us to detect and treat the disease.

(Table 1) indicates that by making a comparison between these studies or different works in this field. And these examinations were conducted over the different years to our time, and through that we can discover the differences between them and the best methods that we can use in the classification process. João R. Sato et.al, (2012) used (SVM) and Minimum Legal Drinking Age (MLDA), with a feature selection algorithm [43]. After imaging, it was discovered that there were 15 affected and 15 non-infected subjects, including 7 women, using pretreatment procedures of SPM2 and VBM. The classifiers achieved an accuracy of 80%, but MLDA uses the highest discriminatory features of 0.1.

peng et al., 2013 used SVM and (ELM) for a 110-subject experimental data set to perform leaving one out of cross-examination. [44] For ADHD classification performance of ELM and SVM for various data set, they extracted and combined data from MRI data. They discovered that the best one has an accuracy of 84.73%. In 2014 Kaung et.al A rating model was created using the ADHD-200 dataset, focusing on fMRI findings and predictions of ADHD [17]. Meanwhile, their findings are consistent with biological research. It's been done too. DBN was tested on an ADHD waiting cohort in the KKI, Peking-1, and NYU, with softmax as classifier. In 2015 Deshpande, Wang, Rangarajan &

Wilamowski, the data are taken as an example to illustrate the usefulness of a fully connected cascade (ANN) architecture for classification performance [45].

In 2019 Mao et al., [46] It showed that the ADHD-200 Consortium public dataset was used to train this method and check whether it was valid or not. In 2020 Gangani Ariyarathne and others, evaluated this study using the four main regions of the DMN by the precision generated by the CNN model [47], and two phases were used in their study, the first phase of the study used correlation images and the second phase used pre-processed images with more variance and made up a larger data set. In 2021, this study deals with the definition of ADHD using resting-state (fMRI) data and also SBC profilin.

W. Saad et al used two methods for the classification by using three different algorithms having the same learning rate and different mini-batch sizes and epochs the first method is the X-rays data set and the second method is the CT dataset. For the X-rays method, they found that the RMs proposed has the best accuracy as it is 90.95%, and also the best accuracy for CT is 91.57% [49].G. Huang et al, made the system which contains three parts [50] to extract the features by using GLCM (Grey Level Coexistence Matrix) and for (Adaboost).

Table 1. Comparison between different works of ADHD detection.

Related Work on ADHD Classification	Classification Technique	Accuracy (%)	Specificity (%)	Sensitivity (%)
ADHD Prediction (Sato et.al,2012) [43]	**SVM, LDA**	**67**	**68.00**	**46.20**
ELM based Classification of ADHD (peng et al., 2013) [44]	**SVM, ELM**	**84.73**		
ADHD Classification (Kuang et al.,2014a; Kuang et al.,2014b) [17]	**DBN**	**72.73**		
FCC ANN for ADHD Classification (Deshpande, Wang, Rangaprakah & Wilamowski,2015) [45]	**FCC ANN**	**90.0**		
ADHD Classification using fMRI (Rubasinghe& Meedeniya, 2020) [1]	**SVM, NB, KNN**	**86.00**		
4D CNN-Based ADHD Classification (Mao et al., 2019) [46]	**4D CNN**	**71.30**	**73.20**	**69.70**
ADHD Classification with SBC (Ariyarathne et al., 2020) [47]	**CNN**	**86.86**	**66.54**	**72.82**
Proposed ADHD-Care_v2 model [48]	**3D CNN**	**85.36**	**66.54**	**72.80**
COVID-19 classification using deep feature concatenation technique [49]	**X-ray (CNN)**	**90.95**	**91.53**	**88.45**
	CT (CNN)	**91.57**	**88.69**	**92.7**
G. Huang et al. [50]	**DenseNet**	**91.72**	**90.63**	**91.65**

We find that the best way after this discussion is CNN. This is because it consists of many hidden layers and does not require any human intervention to supervise it in order to be able to extract its specifications. It also depends on the accuracy of the image classification process. It also reduces computation compared to a regular neural network. CNN networks are used to identify individuals through their photos and verify them in many security operations and can be useful in reducing the number of parameters we need to train and thus improving performance. However, training a neural conversational network is slightly slower than training a DNN. One of the most important features of CNN is the lack of reliance on pre-processing, which reduces the need for human effort to develop its functions. It is easy to understand and quick to implement. It has the highest accuracy among all image prediction algorithms.

7. Conclusion

ADHD is a common psychological condition among children, and it can occur in inheritance and may reach adulthood. Therefore, it is important to early detect and treatment. ADHD is known to have no precise diagnostic mechanism. Early detection of ADHD helps treat affected people. The findings and suggestions of this review will be important for researchers and for many people to provide appropriate treatment. The full research is being done to identify emotions in the different relationships. Therefore, what follows from the results of this study is that it is assumed that more work should be done in this field. However, our findings show that emotion recognition may be a promising target for intervention to enhance positive social performance outcomes. Among preschool children with elevated levels of ADHD behaviors. Future work investigates the unique and interactive effects of children with ADHD behaviors and additional social, emotional, and cognitive skills (e.g., problem-solving, perspective-taking, emotion coping strategies, and executive functioning) on social prediction. Performance is an important next step in this research field. Finally, expansion and investigation of the current study in future work will increase awareness of factors. Therefore, different systems must be designed to obtain better performance and high accuracy, so that this disease can be treated appropriately.

References

1. Rubasinghe, I. D. and Dulani Meedeniya, "A Review of Supportive Computational Approaches for Neurological Disorder Identification," Journal of Neurodevelopmental Disorders, January 2020, pp.271-302, doi:10.4018/978-1-7998-3069-6.ch016.
2. Polanczyk, G.V., et al., "ADHD prevalence estimates across three decades: an updated systematic review and met regression analysis," International journal of epidemiology, January 2014, pp. 434-442, doi: 10.1093/ije/dyt261.
3. Mueller A, Candrian G, Kropotov JD, Ponomarev VA, Baschera GM," Classification of ADHD patients on the basis of independent ERP components using a machine learning system". Nonlinear Biomedical Physics, June 2010, vol.4, pp.1-12, doi: 10.1186/1753-4631-4-S1-S1.
4. Bo Miao, Yulin Zhang, "A feature selection method for classification of ADHD". In proceedings of International Conference Information, Cybernetics Computer Society Systems., July 2017, pp.21–25.
5. Bellec, P., Chu, C., Chouinard-Decorte, F.,et.al, "The Neuro Bureau ADHD-200 Preprocessed repository, "Neuroimaging, January2017, pp.275–286.
6. Arnsten, A. F. T., "The Emerging Neurobiology of Attention Deficit Hyperactivity Disorder: The Key Role of the Prefrontal Association Cortex". The Journal of Pediatric., May 2009, vol.154, no.5, pp.1-2, doi: 10.1016/j.jpeds.2009.01.018.
7. Hamed AM, Kauer AJ, Stevens HE, "Why the diagnosis of attention deficit hyperactivity disorder matters, " Journal of Frontiers in Psychiatry., November 2015, vol.168, no.6, pp.1-10, doi.org/10.3389/fpsyt.2015.00168.
8. Gopikrishna Deshpande, Peng Wang, D Rangaprakash, Bogdan Wilamowski,"Fully Connected Cascade Artificial Neural Network Architecture for Attention Deficit Hyperactivity Disorder Classification from Functional Magnetic Resonance Imaging Dat,"IEEE Transactions on Cybernetics., December 2015, vol.45, no.12, pp.2668-2679, doi:10.1109/TCYB.2014.2379621.

9. E B Cadesky 1, V L Mota, R J Schachar," Beyond words: how do children with ADHD and/or conduct problems process nonverbal information about affect?" In national center for biotechnology information:J Am Acad Child Adolesc Psychiatry, September 2000, vol.39, no.9, pp.1160–1167.
10. Dai, D., et al.," Classification of ADHD children through multimodal magnetic resonance imaging," Frontiers in systems neuroscience, September 2012, vol.6, pp.1-8.
11. Kobel, M., et al.," Structural and functional imaging approaches in attention deficit/hyperactivity disorder: does the temporal lobe play a key role? ", Psychiatry Research: Neuroimaging., August 2010, vol.183, no.3, pp. 230-236, doi: 10.1016/j.pscychresns.2010.03.010.
12. Chang, C.-W., C.-C. Ho, and J.-H. Chen, "ADHD classification by a texture analysis of anatomical brain MRI data". Frontiers in systems neuroscience, September 2012, doi.org/10.3389/fnsys.2012.00066.
13. Ciresan, D., Meier, U. Masci, J. & Schmidhuber, J. "Multi-column deep neural network for traffic sign classification". Journal of Neural Networks, Feburary 2012, pp. 333–338, doi: 10.1016/j.neunet.2012.02.023.
14. Kuang, D., Guo, X., An, X., Zhao, Y., and He, L. "Discrimination of ADHD Based on fMRI Data with Deep Belief Network". In Proceedings of International Conference on Intelligent Computing, 2014, pp.225–232.
15. Metin, B., Krebs, R. M., Wiersema, J. R., Verguts, T., Gasthuys, R., van der Meere, J. J. and Sonuga-Barke, E. "Dysfunctional modulation of default mode network activity in attention-deficit/hyperactivity disorder". Journal of abnormal psychology, 2015, pp.124-208, doi.org/10.1037/abn0000013.
16. DuPaul, Chronis-Tuscano, et al. "Predictors of Receipt of School Services in a National Sample of Youth with ADHD". Journal of Attention Disorders, September 2019, pp.1303-1319, doi 10.1177/1087054718816169.
17. Takeda T., Stotesbery K., Power T., et al. “Parental ADHD Status and Its Association with Proband ADHD Subtype and Severity". The Journal of Pediatrics, December 2010, vol.157, pp.995-1000, doi.org/10.1177/108705471878.
18. Smalley, Susan L, et al. “Familial Clustering of Symptoms and Disruptive Behaviors in Multiplex Families with Attention-Deficit/Hyperactivity Disorder,". Journal of the American Academy of Child & Adolescent Psychiatry, September 2000, vol.39, pp.1135- 1143, doi:10.1111/j.1469-7610.2004.00248. x.
19. Sutskever, I., Martens, J. & Hinton, G. E. "Generating text with recurrent neural networks". In Proc. 28th International Conference on Machine Learning, 2011, pp.1017–1024.
20. Ba, J., Mnih, V. & Kavukcuoglu, K. "Multiple object recognition with visual attention". In Proc. International Conference on Learning Representations, January 2015.
21. W. L. Zhang, R. J. Li, H. T. Deng, L. Wang, W. L. Lin, S. W. Ji, and D. G. Shen, "Deep convolutional neural networks for multi-modality isointense infant brain image segmentation", NeuroImage, March 2015, vol. 108, pp. 214–224.
22. P. Moeskops, M. A. Viergever, A. M. Mendrik, L. S. de Vries, M. J. N. L. Benders, and I. Isgum, "Automatic ˇ segmentation of MR brain images with a convolutional neural network", IEEE Trans. Med. Imaging, 2016, vol. 35, no.5, pp. 1252–1261, doi: 10.1109/TMI.2016.2548501.
23. J. Kleesiek, G. Urban, A. Hubert, D. Schwarz, K. Maier-Hein, M. Bendszus, and A. Biller, "Deep MRI brain extraction: A 3D convolutional neural network for skull stripping", Neuroimaging, 2016, vol. 129, pp. 460–469.
24. D. Zikic, Y. Ioannou, A. Criminisi, and M. Brown, "Segmentation of brain tumor tissues with convolutional neural networks", Proceedings MICCAI Workshop on Multimodal Brain Tumor Segmentation Challenge, Boston, USA, 2014, pp. 36–39.
25. G. Urban, M. Bendszus, F. Hamprecht, and J. Kleesiek, "Multi-modal brain tumor segmentation using deep convolutional neural networks", in Proc. MICCAI BraTS (Brain Tumor Segmentation) Challenge, 2014, pp. 31–35.
26. S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images", IEEE Trans. Med. Imaging, 2016, vol. 35, no. 5, pp.1240–1251, doi:10.1109/TMI.2016.2538465.
27. H. Choi and K. H. Jin, "Fast and robust segmentation of the striatum using deep convolutional neural networks". Neurosis. Methods, 2016, vol. 274, pp. 146–153, doi: 10.1016/j.jneumeth.2016.10.007.
28. A. Prasoon, K. Petersen, C. Igel, F. Lauze, E. Dam, and M. Nielsen, "Deep feature learning for knee cartilage segmentation using a tri-planar convolutional neural network", in Proc. 16th Int. Conf. Medical Image Computing and Computer-Assisted Intervention, Nagoya, Japan, January 2013, pp. 246–253.
29. F. Y. Liu and C. H. Shen, "Learning deep convolutional features for MRI based Alzheimer’s disease classification", arXiv preprint, April 2014.

30. Jie Zhang, Bowen Zheng, Ang Gao, Xin Feng, Dong Liang, Xiaojing Long"A 3D densely connected convolution neural network with connection-wise attention mechanism for Alzheimer's disease classification "Magnetic Resonance Imaging, May 2011, vol.78, pp.119-126.
31. E. Hosseini-Asl, R. Keynton, and A. El-Baz, "Alzheimer’s disease diagnostics by adaptation of 3D convolutional network", in Proc. 2016 IEEE Int. Conf. Image Processing (ICIP), Phoenix, AZ, USA, July 2016, pp. 126–130.
32. Biserka Petrovska, Igor Stojanovic, Tatjana Pano Atanasova-Pacemska, "Classification of Small Sets of Images with Pre-trained Neural Networks" International Journal of Engineering and Manufacturing, pp.40-55, July 2018, doi:10.5815/ijem.2018.04.05.
33. Aly Al-Amyn Valliani, Daniel Ranti, and Eric Karl Oermann." Deep Learning and Neurology: A Systematic Review". Journal of Neurology and Therapy. December 2019, vol. 8, no.2, pp.351-365.
34. Sutskever, I. Vinyals, O. & Le. Q. V. "Sequence to sequence learning with neural networks". In Proc. Advances in Neural Information Processing Systems., 2014, pp.3104–3112.
35. Claire Adam-Bourdarios, Glen Cowan,et.al "The Higgs boson machine learning challenge", JMLR: Workshop and Conference Proceedings., 2015, vol.42, pp.19-55.
36. Y. Yoo, T. Brosch, A. Traboulsee, D. K. B. Li, and R. Tam, "Deep learning of image features from unlabeled data for multiple sclerosis lesion segmentation", in Proc. 5th Int. Workshop on Machine Learning in Medical Imaging, Boston, MA, USA, 2014, pp. 117–124.
37. K. Kamnitsas, C. Ledig, V. F. J. Newcombe, J. P. Simpson, A. D. Kane, D. K. Menon, D. Rueckert, and B. Glocker, "Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation", Journal of Medical Image Analysis, 2017, vol. 36, pp. 61–78.
38. Glover, G. H. 2011. "Overview of functional magnetic resonance imaging". Journal of Neurosurgery Clinics., April 2011, vol.22, no.2, pp.133-139.
39. Long, D., et al.," Automatic classification of early Parkinson’s disease with multi-modal MR imaging". PloS one, 2012. November 2012, vol.7, no.11, pp. 1-9.
40. Sarangi, Susanta; Sahidullah, Md; Saha, Goutam."Optimization of data-driven filterbank for automatic speaker verification”. Journal of Digital Signal Processing. September 2020.
41. Yuan ping, “Recent Advances in Support Vector Clustering: Theory and Applications", In International Journal of Pattern Recognition and Artificial Intelligence., March 2015, vol.29 no.1, pp. 1-29.
42. George J. Knafl, "Adaptive Regression for Nonlinear Interrupted Time Series Analyses with Application to Birth Defects in Children of Vietnam War Veterans", Open Journal of Statistics., , December 2022, vol.12, no.6, DOI:10.1016/j.jclinepi.2020.02.006.
43. Sato, et al "Identification of psychopathic individuals using pattern classification of MRI images", Soc. Neurosci. , 2011, vol.6, pp. 627–639.
44. Peng X, Lin P, Zhang T, Wang J. "Extreme learning machine-based classification of ADHD using brain structural MRI data", PLoS One, November 2013, vol.8, no.11, pp.1-14.
45. Deshpande G, Wang P, Rangaprakash D, Wilamowski B. "Fully Connected Cascade Artificial Neural Network Architecture for Attention Deficit Hyperactivity Disorder Classification from Functional Magnetic Resonance Imaging Data ‘”IEEE Trans Cybern., December 2015, vol 45, no.12.
46. Zhenyu Mao et.al, "Spatio-temporal deep learning method for ADHD fMRI classification", Information Sciences, May 2019.
47. Gangani Ariyarathne, Senuri De Silva,et.al , "ADHD Identification using Convolutional Neural Network with Seed-based Approach for fMRI Data", Conference: ICSCA 2020: 2020 9th International Conference on Software and Computer Applications, , February 2020, pp. 31-35.
48. Senuri De Silva, Sanuwani Dayarathna, et.al, " fMRI Feature Extraction Model for ADHD Classification Using Convolutional Neural Network‘” International Journal of E-Health and Medical Communications, January 2021, vol.12, pp. 81-84, doi:10.4018/ijehmc.2021010106
49. Waleed Saad, Shalaby, W.A., Wafaa A. Shalaby, Mona Shokair, Fathi Abd El-Samie. et al. "COVID-19 Classification using deep feature concatenation technique," Journal of Ambient Intelligence and Humanized Computing, March 2021, vol.13, pp. 2025-2043.
50. Minz A, Mahobiya. "MR image classification using adaboost for brain tumor type". In IEEE 7th International Advance Computing Conference (IACC). 2017, pp. 701-705, doi:10.1109/IACC.2017.0146.