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Detection Attention Deficit Hyperactivity Disorder by using Convolution Neural Network.

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

[1]Communications Department, Faculty of Electronic Engineering, Menoufia University, eman.salah090@gmail.com

[2] Communications Department, Faculty of Electronic Engineering, Menoufia University, Faculty of Engineering, 6-October University. mona.sabry@el-eng.menofia.com.

[3]Communications Department, Faculty of Electronic Engineering, Menoufia University, fathi_sayed@yahoo.com.

[4]Communications Department, Faculty of Electronic Engineering, Menoufia University, engwafaaahmed88@yahoo.com.

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Salah , E.; Shokair, M.; Abd El-Samie , F.; Shalaby , W.

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Abstract: Attention deficit hyperactivity disorder (ADHD) is a neurological disease that is very common in recent times, and many attempts have been made to overcome it. ADHD is diagnosed in boys more than girls. Girls are more likely to have only symptoms of inattention, and less likely to exhibit disruptive behavior that makes ADHD symptoms more noticeable. This means that girls with ADHD may not always be diagnosed. Artificial intelligence has played a very important role in eliminating this disorder using deep learning technology. Deep learning has three algorithms as Deep Neural Network (DNN), convolution neural network (CNN), Recurrent Neural Network (RNN). The disease is diagnosed using functional magnetic resonance imaging (fMRI) to determine whether the person is affected or not by taking some snapshots of brain images. A convolutional neural network (CNN) was chosen to extract the specifications or features of fMRI images.There were an optimization technique of the fMRI datasets namely, Nesterov-Accelerated Adaptive Moment Estimation (Nadam). Using these optimization techniques for adapting the classification system for three CNN network or models for ADHD cases, it was concluded that the accuracy for CNN NET 1 is 97.5%, accuracy for CNN NET 2 is 95% and accuracy for CNN NET 3 is 98.75 %. Finally, it's found that CNN NET 3 is the best as its high accuracy so the system is improved.

Keywords: ADHD, fMRI, CNN, Deep Learning.

1. Introduction

Childhood is a stage of the developmental years that begins at birth and continues through to adulthood. The stage of puberty, is an inevitable stage that every human newborn goes through, where he grows, grows, and develops physically, physiologically, sensory, motor, mentally, psychologically, socially, and religiously in his family and in his surroundings social life in which he lives. It is found that this stage is divided into three stages: early childhood, Intermediate, and late, It has received the attention of researchers and scholars because the child in this stage can encounter various problems that hinder its proper growth [1].

Every research or scientific study has goals and objectives that the researcher seeks to achieve in the end. The search with all its variables includes:

- Detection of hyperactivity disorder and movement and its impact on academic achievement.
- Trying to enrich the educational field with information on this subject, given the seriousness of its spread in our society.

- This research also aims to address in detail the effect of excessive movement on academic achievement.

There are branches and divisions of the concept of artificial intelligence, and perhaps the most famous of these concepts are the machine learning and the deep learning. There are some differences between them [2]. In machine learning a specific device is provided with a set of information called the inputs, and the outputs of the device are called the outputs, the device is well-trained, and we don't manufacture algorithms through machine learning. Suppose that a self-driving car was trained by giving it data about humans, animals, trees, roads, and signaling signs, but in a specific place, for example, Los Angeles in America, after training the car and making the machine learning smart enough to accommodate the road and people. And trees, and we later drove this car in Australia, for example. The expected result is that the car will run efficiently because the machine has learned and gained experience through the previous data, and it can be used in any other field [3].

Deep learning is part of machine learning. Somewhere inside the Machine Learning there is Deep Learning, a qualified layer that allows to study that data more deeply, to perform the most complex and difficult computations [4].

Deep Learning comes to analyze the data and create new accounts through a lot of information. This information is provided by machine Learning and transmitted through the Neural Networks as we indicated. Then, when Machine Learning is configured, several of them can be collected in one device to get the Artificial Intelligence or artificial intelligence [5].

The result of ADHD is that it interferes with job performance or development at work [6]. ADHD primary care providers can show affected people to mental health professionals such as psychiatrists and psychologists, who have the ability to diagnose the affected person's health condition and provide appropriate treatment. In order to be diagnosed with the condition, the affected person must have had symptoms for an extended period of time. Therefore, a comprehensive evaluation is necessary to determine the cause of the symptoms. Most children with ADHD are diagnosed during their school years [7]. These symptoms appear in particular in stages 3 to 6 and may persist into adulthood and adolescence. [8] By the time a child reaches elementary school, symptoms of inattention may become more pronounced and cause the child to struggle academically. Any teen with ADHD also struggles with antisocial relationships and behaviors. Inattention, anxiety, and impulsiveness tend to persist into adulthood [9].

Some people have noticed that this disorder appears in adulthood gradually in childhood first, and may continue into adulthood [10-11]. But the way ADHD affects adults can differ from the way it affects children [12]. These symptoms can cause significant problems in a child's life, such as poor academic achievement, poor social interaction with other children and adults, and discipline problems [13-14].

Classification or categorization is done using a convolutional neural network [15-16]. Many relevant studies [17-18] to classify ADHD rely on electroencephalography (EEG), fMRI, and eye movement data. The high incidence of ADHD in children with clinical symptoms will continue into adulthood by showing destructive elements due to the lack of appropriate treatments [19].

As they get older, children must learn to improve their attention and self-control. To classify MRI images, neural networks were used in many studies [20]. CNNs are regular versions of layered cognition. Layered cognition usually means fully connected networks, that is, every neuron in one layer is connected to all neurons in the next layer [21-22].

Also, this research will explain ADHD and how to overcome it using one of the Deep Learning algorithms. The classification of this disorder has been done using the latest types of modern medical imaging and thus can contribute significantly to getting rid of this disease.

The remaining parts of this paper are organized as follows: Relevant work will be presented in Section 2. The main structure of the proposed framework will be described in Section 3. Experimental results was introduced in section 4 and discussions will be conducted in Section 5. Finally, conclusions will be made in Section 6.

2. Related Work

Artificial intelligence has been developed to obtain data and algorithms for diagnosing hyperactivity disorder and attention deficit hyperactivity disorder. A number of different studies have been mentioned in which artificial intelligence was developed using the Neuro Bureau ADHD 200 data set, but in this research, 400 images taken by Magnetic Resonance Imaging (MRI) were used [23-24-25-26]. Many studies have been done by others to diagnose this disease such as Miao et al. dealt with different combinations of fractional amplitude of low-frequency fluctuation (fALFF), Resting-State Networks (RSN), Default Mode Network (DMN) and Regional homogeneity (ReHo), whose accuracy was able to achieve an accuracy of up to 67% [27]. Using Electroencephalography (EEG), a Support Vector Machine (SVM) classifier for adult ADHD classification, an accuracy of 73% was obtained by considering different scenarios at rest [28].

Deep learning approaches have been directed to classify ADHD in many different domains spanning deep belief networks (DBN), deep Bayesian networks (BN), convolutional neural networks (CNN), and artificial neural networks (ANN) [29]. Several studies have analyzed fMRI data to reveal the relationship between tasks performed during the scan and brain activation. As mentioned above, different data sets and algorithms are used and researched to classify ADHD. However, studies on the classification of ADHD using skeletal data have not yet been performed. Skeletal data includes the joint movements of the subject, but a deep learning-based Convolution Neural Network algorithm was used to classify ADHD groups and normal groups. Evaluation of radiological images is a specialized activity that requires a radiologist. Artificial intelligence for displaying radiological images is one of the main topics [30]. LeNet-5, a pioneering 7-level convolutional network created by LeCun et.al, AlexNet was designed by the SuperVision group, consisting of Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever, VGGNet consists of 16 convolutional layers and is very attractive because of its highly unified architecture, and The residual neural network (ResNet) from Kaiming He et al introduced a new architecture with 'skipping connections' and features heavy batch normalization [31]. Classification using MRI technology using various machine learning classifiers, including Support Vector Machine (SVM), Gradient Boost, K Nearest Neighbor (KNN), and Logistic Regression [32]. Classification of brain tumors is an important issue in computer-aided diagnosis (CAD) for medical applications a fairly high performance was recorded [33]. Interpreting prefixes in convolutional neural networks as an intermediate step between regular convolution and the deeply separable convolution process (deep convolution followed by point convolution) [34].

3. System Design

Artificial intelligence, especially deep learning, was able to correctly diagnose the disease in 87% of cases. In this research, one of the deep learning algorithms was used, which is the CNN, and through it, an image classification is made using MRI. Which takes a group of images of some people, and the CNN performs a scanning process of the images, which is known for examining every part in the image, as the image is a phrase. Using a matrix containing a group of pixels so that it can determine the locations of the infection, and from here the disease is diagnosed and the appropriate treatment is determined.

Convolutional neural networks (CNNs) are an important component of deep learning .They allow computers to understand images and other visual data. We can train computers to spot patterns and identify objects based on what they "see" by using CNNs in deep learning. An ADHD profile was constructed by fMRI data known as the ADHD Care V1. ADHD 200-Global Competition fMRI data was used. An efficient CNN architecture was developed, where it's improved accuracy. And also, three models were created namely:

i. CNN NET 1
In Figure (1) the neural network was created with a convolution layer of 64 filters with 7*7 kernel size and with the activation function of 'Relu'. The second Layer is max pooling with the size of 5*5 and the third layer is also a convolution layer which a has filter of 128a with 5*5 kernel size and the last layer is average pooling that has a size of 14*14.

ii. CNN NET 2
In Figure (1) the neural network was created with a convolution layer of 64 filters with 7*7 kernel size and the activation function of 'Relu'. The second layer was created by 64 filters with 5*5 convolutions and with the same specification as the first layer. Then the third layer of 128 filters with 3*3 kernel size as the fourth layer is also a convolution layer with 12filterser and 3*3 convolutions with an average pooling of 11*11.

iii. CNN NET 3 or Addition
It resulted from combining the two models together, where high accuracy will be obtained and the system will be greatly improved. And also it has 27 layers as it is shown in Table 1.

Finally, a fully connected softmax activation function is added to enable classification

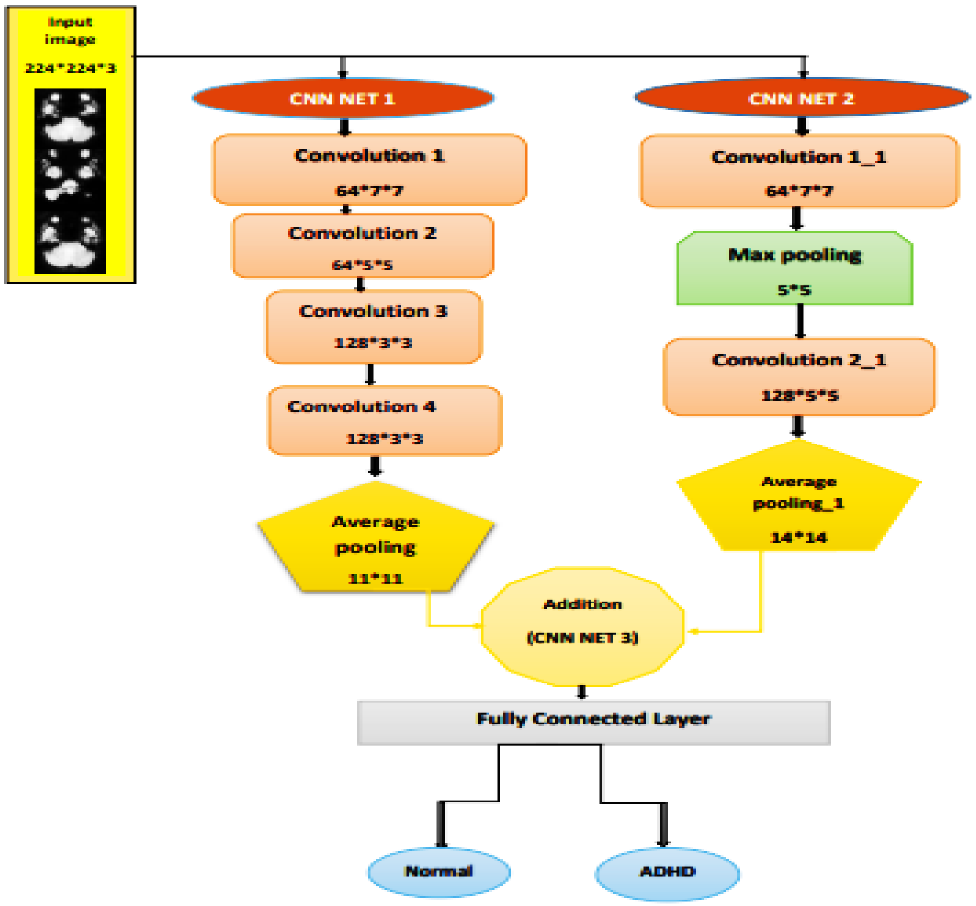

Figure 1: System Design.

CNNs have several layers such as convolution, max pooling, intermediate pooling blocks, and SoftMax layers. Table 1 briefly describes the basic rule for those layers, where This table was actually deduced using the MATLAB program in the stage of creating the network, or what is called system design. This tour explains the stages of convolutional neural networks and shows the size of the image at each stage. There are four basic operations in ConNet: Convolution, Non-Linearity (or as you know it using ReLU), Pooling or Subsampling, and Classification (to be in the full contact class) Classification. These four processes are fundamental to all anatomical networks and each step will be explained in a simplified way to make it easier to fully understand.

1. Convolution Layer
   The primary goal of the convolution process in the case of ConvNet is to extract features from the input image, so that the convolution or filtering process preserves the spatial relationship between pixels in the image by learning the image features using small boxes (kernels) on the input data.
2. Non linearity or (Relu)
   An additional process called ReLU is used after each convolution. ReLU stands for Rectified Linear Unit and is a non-linear operation.
3. Pooling or Subsampling
   Spatial aggregation, or as it is also known as subsampling or downsampling, reduces the dimensions of each feature map while keeping the important information. Spatial aggregation has several types, such as: Max (the highest value), Average (calculating the average), Sum (the sum) … etc
4. Fully Connected Layer
   The fully connected layer is a traditional multilayer layer that uses the softmax activation function in the output layer. The term “fully connected” indicates that every neuron in the previous layer is connected to every neuron in the next layer. The outputs from the convolution and pooling layers represent high-level properties of the input image. So the goal of the fully connected layer is to use these properties to classify the input image into several classes based on the training data.

Table 1: Description of the proposed CNN model

ANALYSIS RESULT				
	Name	Type	Activations	Learnables
1	Inp 224×224×3 images with 'zero center' normalization	Image Input	224(S)×224(S)×3(C) × 1(B)	-
2	Conv 1 64 7×7 convolutions with stride [1 1] and padding 'same'	2-D Convolution	218 (S) × 218(S) × 64 (C) × 1(B)	Weights 7×7×3… Bias 1×1×64
3	bn1 Batch normalization	Batch Normalization	218 (S) × 218(S) × 64 (C) × 1(B)	Offset 1×1×64 Scale 1×1×64
4	relu1 Relu	Relu	218 (S) × 218(S) × 64 (C) × 1(B)	-
5	conv2 64 5×5 convolutions with stride [2 2] and padding [0 0 0 0]	2_D Convolution	107 (S) × 107(S) × 64 (C) × 1(B)	Weights 5×5×64 Bias 1×1×64
6	bn2 Batch Normalization	Batch Normalization	107 (S) × 107(S) × 64 (C) × 1(B)	Offset 1×1×64 Scale 1×1×64
7	relu2 Relu	Relu	107 (S) × 107(S) × 64 (C) × 1(B)	-
8	conv3 128 3×3 convolutions with stride [3 3] and padding [0 0 0 0]	2_D Convolution	35(S) × 35(S) × 128 (C) × 1(B)	Weights 3×3×64 Bias 1×1×128
9	bn3 Batch normalization	Batch Normalization	35(S) × 35(S) × 128 (C) × 1(B)	Offset 1×1×128 Scale 1×1×128
10	relu3 Relu	Relu	35(S) × 35(S) × 128 (C) × 1(B)	-
11	Conv 4 256 3×3 convolutions with stride [2 2] and padding [0 0 0 0]	2_D Convolution	11(S) × 11(S) × 128 (C) × 1(B)	Weights 3×3×128… Bias 1×1×128
12	bn4 Batch Normalization	Batch Normalization	11(S) × 11(S) × 128 (C) × 1(B)	Offset 1×1×128 Scale 1×1×128
13	relu 4 Relu	Relu	11(S) × 11(S) × 128 (C) × 1(B)	-
14	Conv1_1 64 7×7 convolutions with stride [1 1]	2_D convolution	218(S) ×218(S)×64(C)×1(B)	Weights 7×7×3.. Bias 1×1×64
15	bn1_1 Batch Normalization	Batch Normalization	218(S) ×218(S)×64(C)×1(B)	Offset 1×1×64 Scale 1×1×64
16	relu1_1 Relu	Relu	218(S) ×218(S)×64(C)×1(B)	-
17	Maxpool 5×5 max pooling with stride [3 3]	2_D Max pooling	73(S) ×73(S)×64(C)×1(B)	-
18	Conv2_1 128 5×5 convolutions with stride [5 5]	2_D convolution	14(S) ×14(S)×128(C)×1(B)	Weights 5×5×64 Bias 1×1×128
19	bn2_1 Batch Normalization	Batch Normalization	14(S) ×14(S)×128(C)×1(B)	Offset 1×1×128 Scale 1×1×128
20	relu2_1 Relu	Relu	14(S) ×14(S)×128(C)×1(B)	-
21	Avgpool 11×11 average pooling with stride [2 2] and padding [0 0 0 0]	2_D Average Pooling	1(S) ×1(S)×128(C)×1(B)	-
22	Avgpool_1 14×14 average pooling with stride [2 2]	2_D Average Pooling	1(S) ×1(S)×128(C)×1(B)	-
23	Addition Element-wise addition of 2 inputs	Addition	1(S) ×1(S)×128(C)×1(B)	-
24	Dropl 70% dropout	Dropout	1(S) ×1(S)×128(C)×1(B)	-
25	Fullyconnect 2 fully connected layer	Fully Connected	1×1×2	Weights 2×256 Bias 2×1
26	Soft Softmax	Softmax	1×1×2	-
27	Out Crossentropyex	Classification Output	-	-

4. Results

Deep Learning solves the data and creates new accounts through a lot of information. This information is provided by machine Learning and transmitted through the Neural Networks as indicated. Then, when the Machine Learning is configured, several of them can be combined into one device to get the Artificial Intelligence. CNNs process images faster and more efficiently than traditional processes. This is the result of pooling layers, which reduce the number of parameters required to process the image. In this way, they reduce memory usage and processing costs. Many regions use CNNs, such as; face recognition, video classification, and image analysis.

In this study, classification of ADHD, and normal groups was performed using the CNN model using ADHD-200 data as input data. Moreover, in this paper, accuracy, precision, recall, and the F1 score were used to evaluate the model. The matrix shows the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) produced by the model on the test data, equation (1),(2),(3),(4) as follows:

$$Accuracy = \frac{T_p+T_N}{T_p+T_N+F_p+F_N} \tag{1}$$

$$Precision = \frac{T_p}{T_p+F_p} \tag{2}$$

$$Recall = \frac{T_p}{T_p+F_N} \tag{3}$$

$$F1 - Score = \frac{2*precision*Recall}{Precision+Recall} \tag{4}$$

There are only three optimization algorithms that have been used for the proposed CNN. Figure (2), shows a comparison between CNN NET 1, CNN NET 2, and CNN NET 3, where for CNN NET 1, accuracy is approximately equal to 97.5 %, precision is 100%, recall is 98.73 % and F-score is 97.43 %, CNN NET 2 accuracy is roughly equal to 95%, Precision is 92.76%, recall is 96.61%and F-score is 95.08%, and also for CNN NET 3 is typically equal 98.75%, precision is 98.75%, recall is 98.75% and F-score is 98.75%.

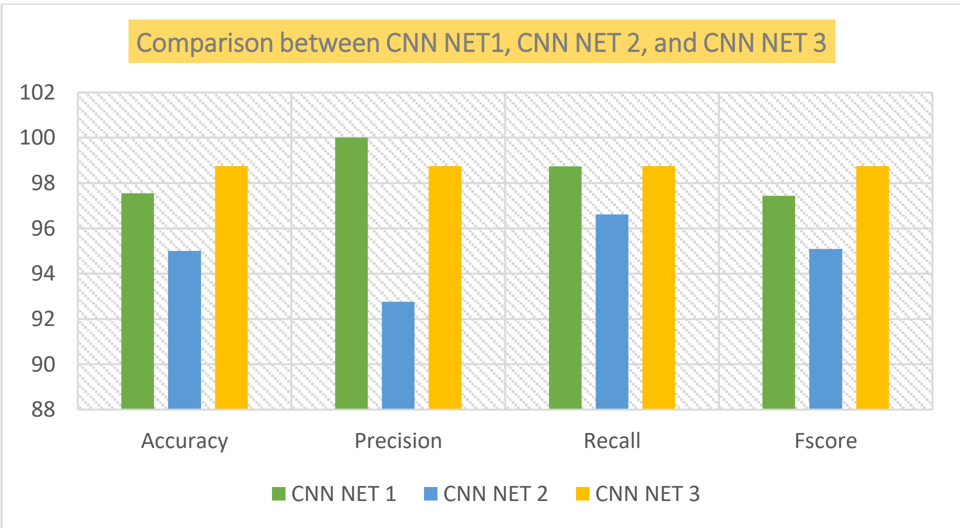

Figure 2: Performance of the Proposed CNN for fMRI Dataset under CNN NET1, CNN NET 2, and CNN NET 3 optimization algorithm.

5. Discussion

This part discusses ADHD detection performance. It is evaluated by knowing the accuracy, resolution, recall, and f1 score. Three models were done in order to improve the performance of the system as the performance of the system increases with increasing accuracy. The data set used for ADHD is 200 images and for normal cases, it is 200 images. The matrix is only used for testing The accuracy of each algorithm. To classify all ADHD pictures, they will be combined into one category, the training data set and test data set are 20% and 80%, respectively. Confusion matrices are considered as if they were a color-coded heat map using the seaborne library. Sometimes losing training, validation, and accuracy is not enough to know the performance of the validation data.

One way is to visualize with a confusion matrix. Figures (3), (4), and (5) depict the confusion matrix and graphical comparison of the confusion matrix of CNN NET 1, CNN NET 2, and CNN NET 3.

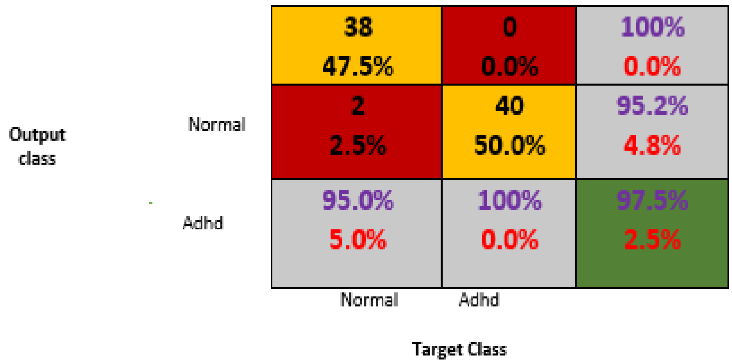

Figure 3: Confusion Matrix for CNN NET 1

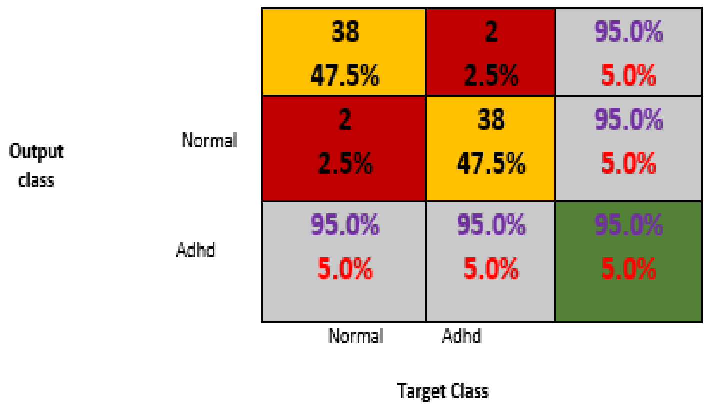

Figure 4: Confusion Matrix for CNN NET 2.

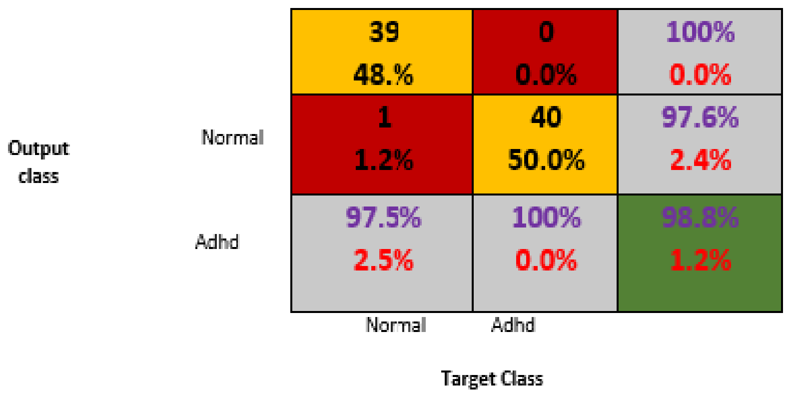

Figure 5: Confusion Matrix for CNN NET 3.

In Table 2, a comparison is presented between the work of others and the model proposed in this research to clarify the difference between them and to conclude with higher accuracy. It was concluded that the algorithm used produces higher accuracy than the others.

Table 2. Comparison of different work-ups for ADHD screening

References	Method	Accuracy %	Precision %	Recall %	F-score %
Deepak and Ameer [30]	Min-max normalization, with SVM and KNN classifier	91	82.1	3.5	92.2
Raju et al. [31]	Bayesian fuzzy clustering segmentation with HSC-based multi SVNN classification method	93	90.87	91.65	92.40
K. Kamnitsas et al. [32]	DeepMedic	94.98	93.77	94.04	95.23
T. W. Huang et al.[33]	Mrbrain	95.51	94.90	94.22	95.3
S. Das [34]	AlexNet	93.14	92.43	95.78	94.07
Proposed Model-CNN NET 1	CNN	97.5	100	98.73	97.43
Proposed Model-CNN NET 2	CNN	95	92.76	96.61	95.08
Proposed Model-CNN NET 3	CNN	98.75	98.75	98.75	98.75

6. Conclusions

This paper talks about attention deficit hyperactivity disorder and attention deficit disorder, how to detect diseases, what are its symptoms, and ways to deal with it. It is important for practitioners to be aware of the positive and negative effects of this disease and how it can affect their lives. It is necessary to delve deeper into this area to explore patients' reactions to receiving treatment, that there is a diagnosis for this disease, as well as opinions regarding late diagnosis and late treatment as well. The use of fMRI in ADHD research is having a clear impact .This paper addressed fMRI image processing, feature extraction, and classification based on the selection of optimal data processing methods and feature extraction based on seed correlation, ReHo, and fALFF for CNN, a learning model based on considering the coordinates of the entire DMN region. This paper also shows that one of the deep learning algorithms was used to detect the disease by creating Three networks and determining which one has the highest accuracy, and accordingly, it is used in diagnosing this disorder and receiving appropriate treatment.

References

1.Masako Nagata, Tomohisa Nagata, Akiomi Inoue, et.al "Effect Modification by Attention Deficit Hyperactivity Disorder (ADHD) Symptoms on the Association of Psychosocial Work Environments With Psychological Distress and Work Engagement" .Frontiers in Psychiatry, March 2019.
2. Patrick Grieve," Deep learning vs. machine learning: What's the difference?" Zen desk Blog, May 2023.
3. Batta Mahesh, "Machine Learning Algorithms -A Review ", International Journal of Science and Research (IJSR), January 2020, vol.9, pp. 381-386.

4. Laith Alzubaidi, Jinglan Zhang, Amjad J. Humaidi, et.al " Review of deep learning: concepts, CNN architectures, challenges, applications, future directions" , Journal of Big Data, 2021, vol.8, no.53.
5. ly 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.
6. Singh A, Yeh CJ, Verma N, Das AK. "Overview of Attention Deficit Hyperactivity Disorder in Young Children". Health Psychol Research, April 2015, vol.3, no.2.
7. Eloyan A, Muschelli J, Nebel M B, et al. "Automated diagnoses of attention deficit hyperactive disorder using magnetic resonance imaging". , Frontiers in System Neuroscience, 2012.
8. Wolf R C, Plichta M M, Sambataro F, et al.,"Regional brain activation changes and abnormal functional connectivity of the ventrolateral prefrontal cortex during working memory processing in adults with attention deficit/hyperactivity disorder". Human brain mapping, 2009, vol.30, no.7, pp. 2252-2266.
9. Diana S. Cortes, Petri Laukka, Christina Lindahl ،and Håkan Fischer's "Memory for faces and voices varies as a function of sex and expressed emotion". PLOS ONE, Junne 2017, vol.12, no.6.
10. Bergwerf CE, Luman M, Weeda WD, Oosterlaan J, "Neurocognitive profiles in children with ADHD and their predictive value for functional outcomes", National Library of Medicine, 2019, vol.23, no.13, pp.1567–1577.
11. Gire C, Garbi A, Zahid M, Beltran Anzola A, Tosello B, Datin-Dorrière V " Neurobehavioral Phenotype and Dysexecutive Syndrome of Preterm Children: Comorbidity or Trigger? An Update", Multidisciplinary Digital Publishing Institute (MDPI), February 2022, vol.9, no.2.
12. Ana-María Soler-Gutiérrez, Juan-Carlos Pérez-González, and "Evidence of emotion dysregulation as a core symptom of adult ADHD: A systematic review", PLOS ONE, January 2023, vol.18, no.1.
13. Michael.Milham, faird, et.al "The ADHD-200 Consortium: A Model to Advance the Translational Potential of Neuroimaging in Clinical Neuroscience", Frontiers in Systems Neuroscience, September 2012, vol.6.
14. Wolf R C, Plichta M M, Sambataro F, et al., "Regional brain activation changes and abnormal functional connectivity of the ventrolateral prefrontal cortex during working memory processing in adults with attention deficit/hyperactivity disorder" Journal of Human brain mapping, 2009, vol. 30, no.7, pp. 2252-2266.
15. Rebecca L. Stephens, Heba E. Elsayed, J. Steven Reznick, et.al "Infant Attentional Behaviors Are Associated With ADHD Symptomatology and Executive Function in Early Childhood, SAGE Journal of Attention Disorder, November 2021, vol.25, no.13, pp.1908-1918.
16. Walz G, Blazynski N, Frey L,et.al," Long-Term Effects of an Oligoantigenic Diet in Children with Attention-Deficit/Hyperactivity Disorder (ADHD) on Core Symptomatology", Nutrients, December 2022, vol.14, no.24.
17. Kirova A-M, Kelberman C, Storch B, DiSalvo M, Woodworth KY, Faraone SV, Biederman J, "Are subsyndromal manifestations of attention deficit hyperactivity disorder morbid in children? A systematic qualitative review of the literature with meta-analysis" Psychiatry Res, 2019, vol. 274, pp.75–90.
18. McConaughy SH, Volpe RJ, Antshel KM, Gordon M, Eiraldi RB, "Academic and social impairments of elementary school children with attention deficit hyperactivity disorder". School Psychology Review, 2011, vol.40, no.2, pp.200–225.
19. Harish Singanamala, Naveen Kumar P. et.al "Study of prevalence and factors affecting the prevalence of attention deficit hyperactivity disorder in primary school children, International Journal of Contemporary pediatrics, ", May 2021, vol.8, no.5.
20. Nijmeijer JS, Minderaa RB, Buitelaar JK, Mulligan A, Hartman CA, Hoekstra PJ "Attention-deficit/hyperactivity disorder and social dysfunctioning". Clin Psychol Rev, 2008, vol.28, n0.4, pp.692–708.
21. Zou, L., Zheng, J., Miao, C., Mckeown, M., & Wang, Z., "3D CNN Based Automatic Diagnosis of Attention Deficit Hyperactivity Disorder Using Functional and Structural MRI. IEEE Access": Practical Innovations, Open Solutions, 2017, pp. 23626–23636.
22. Takahashi, N., Gygli, M., Pfister, B., & Van Gool, L., "Deep convolutional neural networks and data augmentation for acoustic event detection". arXiv preprint, 2016.
23. Zhao, K.; Duka, B.; Xie, H., et al "A dynamic graph convolutional neural network framework reveals new insights into connectome dysfunctions in ADHD". Neuroimage, 2022.
24. Riaz, A.; Asad, M.; Alonso, E.; Slabaugh, G. "Deep fMRI: End-to-end deep learning for functional connectivity and classification of ADHD using fMRI", Journal of Neurosci, 2020.
25. Luo, Y.; Alvarez, T.L.; Halperin, J.M.; Li, X. "Multimodal neuroimaging-based prediction of adult outcomes in childhood-onset ADHD using ensemble learning techniques". NeuroImage Clin, 2020.
26. Sun, Y.; Zhao, L.; Lan, Z.; Jia, X.-Z.; Xue, S.-W." Differentiating boys with ADHD from those with typical development based on whole-brain functional connections using a machine learning approach." Neuropsychiatr. Dis. Treat, 2020, vol.16, pp.691
27. Nigg JT, Karalunas SL, Feczko E, Fair DA, " Toward a revised nosology for ADHD heterogeneity". Biol Psychiatry Cogn Neurosci Neuroimaging, 2020
28. Behrad TaghiBeyglou a, Ashkan Shahbazi b, Fatemeh Bagheri c, Sina Akbarian d, Mehran Jahed,"Detection of ADHD cases using CNN and classical classifiers of raw EEG", ELSEVIER, 2022, vol.2.

29. Anjali D Deshpande, Marcie Harris-Hayes, Mario Schootman, "Epidemiology of diabetes and diabetes-related complications", Phys Ther., 2008.
30.C. Szegedy, S. Ioffe, V. Vanhoucke, and A. Alemi, "Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning," Association for the Advancement of Artificial Intelligence, vol. 4, pp. 12, Feburary. 2016.
31. Siddhartha Das, "CNN Architectures: LeNet, AlexNet, VGG, GoogLeNet, ResNet and more". Analytics Vidhya, November 2017.
32. Minz A, Mahobiya. "MR image classification using adaboost for brain tumor type". In IEEE 7th International Advance Computing Conference (IACC)., pp. 701-705, 2017.
33. S Deepak, P M Ameer. "Brain tumor classification using deep CNN features via transfer learning". Comput Biol Med., (2019).
34. F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1800-1807, 2017.