International Journal of Engineering and Applied Science October 6 University
https://ijeasou.journals.ekb.eg/
Online ISSN 3009-6448
Volume (2),Issue(1)
January 2025, pp:68-79

A High-Precision FMRI-CNN Framework with Advanced Classification Techniques for Improved ADHD Diagnosis

Eman Salah[1], Mona Shokair[1, 2], M. Mokhtar Zayed*[1, 3], Ahmed Elkorany[1] and Wafaa A. Shalaby[1]

[1] Department of Communications, Faculty of Electronic Engineering, Menoufia University, Menouf City, Menoufia Governorate, Egypt.
[2] Department of Electrical Engineering, Faculty of Engineering, October 6 University, 6th of October City, 12585, Giza, Egypt.
[3] Department of Communications and Computers Engineering, Higher Institute of Engineering, El-Shorouk Academy, El-Shorouk City, Cairo Governorate, Egypt.
* Corresponding author’s email: mohammed.mokhtar.zayed@gmail.com

https://doi.org/10.21608/ijeasou.2025.349267.1039

Received:31 December 2024
Accepted:12 January 2025
Published:12 January 2025

Abstract – Attention Deficit Hyperactivity Disorder (ADHD) is a prevalent public health issue that impacts individuals globally. Characterized by symptoms such as inattentiveness, hyperactivity, and impulsivity, ADHD often persists throughout life, significantly affecting an individual's social, educational, and occupational functioning. It is frequently associated with various mental health challenges, including disruptive behaviors, emotional dysregulation, and an increased risk of self-harm, emphasizing the importance of early and accurate diagnosis. This paper presents a diagnostic approach leveraging Functional Magnetic Resonance Imaging (fMRI) enhanced with optical amplification for ADHD detection. By utilizing Convolutional Neural Networks (CNNs), this method extracts essential features from fMRI data to improve diagnostic accuracy. The study further explores the efficacy of three optimization algorithms—Maximum Adaptive Moment Estimation (AdaMax), Accelerated Nesterov Adaptive Moment Estimation (Nadam), and Root Mean Square Propagation (RMSProp)—to refine classification outcomes. Experimental results demonstrate that RMSProp yields the highest accuracy at 98.33%, surpassing leading architectures such as ResNet (95.83%) and GoogleNet (93.55%). These findings mark a significant advancement in automated ADHD diagnosis, offering a robust, high-accuracy method that could streamline clinical assessments and provide earlier intervention opportunities to mitigate long-term adverse effects associated with the disorder.

Keywords: ADHD, Public health concern, FMRI, CNNs, Optimization techniques.

I. Introduction

Nowadays, ADHD has taken a large part of the attention of many people due to its widespread in recent times [1],[2], as the incidence of this disease increases annually, and it is important to detect it early so that it does not negatively affect neurological development [3],[4]. There is more than one test to conduct the diagnosis process to determine if the child has ADHD [5],[6]. FMRI has an effective role in identifying and detecting this disorder [7],[8]. Thus, taking a set of medical images useful for diagnosing the type of injury. They are presented to the specialist doctor, and he explains the method of dealing with the disease and ways to overcome it. In fact, infected people always cannot control themselves or their emotions in a correct way, so they are always exposed to problems [9]. Some medical examinations are conducted, including hearing and vision examinations, to identify this disease [10]. The diagnosis of the disease is made through discussions with the child’s parents, emphasizing details about the child, such as their birthdate and their social interactions with both people and objects [11]. For classification, FMRI is employed alongside specialized CNNs designed for learning, as seen in the references. [12]-[29]. The glass fiber core is surrounded by another layer of glass called cladding. During the transmission of the signal from the transmitter to the receiver, a weakness in the signal may occur, and this weakness is compensated for by the optical amplifier. Optical FMRI (OFMRI or OPTO-FMRI) is an imaging technique based on hemodynamics, enabling the indirect assessment of neural activity and the observation of brain-wide circuits under particular cellular modulation [30]. Consequently, FMRI technology is integrated with optical amplification to enhance blood-oxygen level-based functional FMRI.

I.1. Motivation

ADHD is a prevalent and enduring mental health disorder that impacts individuals throughout their lives, contributing to a broad range of emotional and behavioral challenges, including self-harm and antisocial behavior. However, one of the most critical issues in managing ADHD is ensuring an accurate and timely diagnosis. Delays in diagnosis can exacerbate these issues, hindering early intervention and proper treatment. Traditional diagnostic methods, while useful, can be subjective, slow, and insufficient in providing a definitive diagnosis. To address these limitations, there is an urgent need for more effective and precise methods for ADHD detection. This study aims to enhance ADHD diagnosis by integrating FMRI with advanced CNNs and optimization techniques, thereby providing a high-accuracy diagnostic tool that can support early intervention efforts and improve treatment outcomes.

I.2. Key Contributions

The primary contributions of this paper are sixfold:

1. **FMRI-CNN Hybrid Diagnostic Method:** Introduces an innovative approach combining FMRI with CNNs for accurate and efficient detection of ADHD.
2. **Optimization Techniques for Classification:** Examines three optimization algorithms—AdaMax, Nadam, and RMSProp—tailored to FMRI image data to enhance the performance of the classification model.
3. **Superior Accuracy Achievement:** Achieves a remarkable classification accuracy of 98.33%, outperforming other deep learning models such as ResNet (95.83%) and GoogleNet (93.55%), demonstrating the effectiveness of the proposed approach.
4. **RMSProp Optimization for Improved Performance:** Identifies RMSProp as the most effective optimization technique, resulting in higher accuracy for classifying ADHD cases compared to AdaMax and Nadam.
5. **Efficient Feature Extraction:** Utilizes CNNs to extract meaningful features from FMRI scans, enabling precise identification of brain patterns associated with ADHD, which enhances diagnostic reliability.
6. **Practical Implications for ADHD Diagnosis:** Offers a new pathway for the early and accurate diagnosis of ADHD, contributing to faster intervention, improved therapeutic outcomes, and a better understanding of the disorder's neural characteristics.

I.3. Literature Review

The following is a summary of the literature review presented in this paper:

As stated in [31], the study introduced the first successful application of direct electromechano-optical transduction in a Magnetic Resonance (MR) system, facilitating MR imaging through direct optical detection and amplification of the MR induction signal. The findings yielded clear images and spectra for the tested phantom and coil, with noise levels corresponding to the Lorentzian linewidth of mechanical motion and optical noise. While the current signal-to-noise ratio and bandwidth of the transducer are lower than those of commercial systems, improvements can be achieved by increasing the RF bias amplitude, minimizing parallel capacitance, and optimizing the membrane-capacitor gap. Further reductions in noise and enhancements in bandwidth could be obtained by cooling the system, boosting the mechanical quality factor, using lighter membranes, and refining the optical cavity.

As highlighted in [32], the study conducted a review of existing literature on the application of machine learning (ML) and deep learning (DL) in ADHD diagnosis, categorizing the studies based on diagnostic tools such as brain MRI, physiological signals, questionnaires, game simulators, and motion data. The review identified key gaps, including the limited availability of public datasets for most diagnostic modalities except for MRI, and a lack of attention to data from wearable devices such as ECG, PPG, and motion sensors. The study recommended the creation of additional public datasets and the development of AI models that integrate data from wearable devices to enhance ADHD diagnosis and monitoring, ultimately aiming to create a comprehensive AI-based clinical decision support system for ADHD.

The authors of [33] proposed the use of an extreme learning machine (ELM) algorithm to enhance the diagnosis of ADHD, aiming to overcome the limitations of traditional methods. They analyzed MRI data from 55 ADHD patients and 55 healthy controls, extracting 340 cortical features. The performance of the ELM algorithm was compared with that of support vector machine (SVM) approaches. The ELM demonstrated superior prediction accuracy of 90.18%, outperforming SVM with 84.73% (SVM-Linear) and 86.55% (SVM-RBF), highlighting its greater efficiency and robustness. Significant differences in brain features were observed between ADHD patients and healthy controls in the frontal, temporal, occipital, and insular regions. These findings suggest that ELM is a promising method for ADHD diagnosis and could potentially be applied to other neurological conditions.

Reference [34] explored how the ADHD status of fathers and mothers' influences ADHD symptoms and subtypes in children. The study, which analyzed data from 323 families, revealed that 23% of fathers and 27% of mothers had ADHD, with 41% of children having at least one parent with the disorder. Children of parents with ADHD displayed more severe symptoms. Paternal ADHD was associated with a higher likelihood of the combined ADHD subtype and a lower likelihood of the inattentive subtype in male children. The study concluded that parental ADHD influences symptom severity in different ways depending on the parent's gender, but there is a weak correlation between the self-reported ADHD status of parents and the severity of their child's condition. Additionally, having both parents with ADHD did not significantly increase the severity of the child's symptoms.

In [35], the authors introduced an automated ADHD diagnostic approach that utilizes resting state functional MRI (rs-fMRI) data combined with a 4-D CNN model incorporating spatio-temporal deep learning techniques. The method applies granular computing to analyze time-series 3-D frames from rs-fMRI, integrating feature pooling, LSTM, and spatio-temporal convolution. By augmenting the dataset and training on the ADHD-200 Consortium dataset, the model achieved an accuracy of 71.3% and an AUC of 0.80, surpassing traditional diagnostic methods. These findings indicate that this deep learning-based technique can greatly enhance the accuracy of automatic ADHD diagnosis by directly learning brain motion patterns from the data.

The paper is organized as follows: **Section II** describes the core structure of the proposed system. **Section III** presents the empirical results and provides a discussion of the findings. Lastly, **Section IV** concludes the paper and offers recommendations for future research.

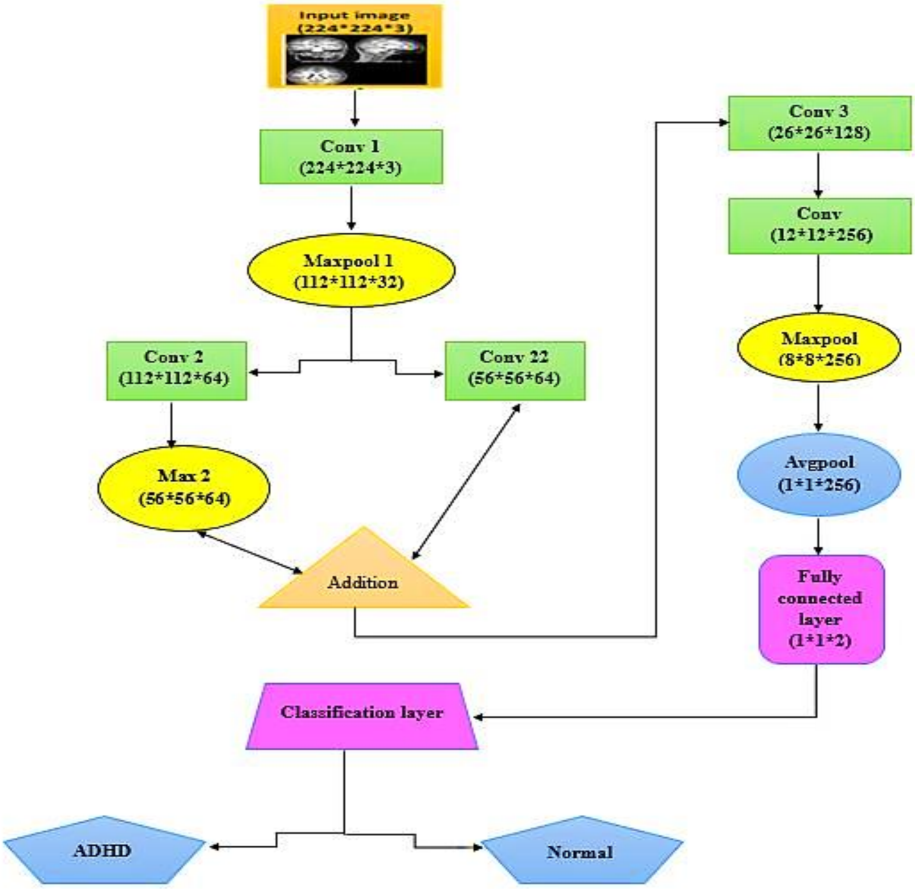

Fig. 1. The brain image segmentation and classification system's structure are founded on CNN for the proposed method.

II. The Suggested System

The fundamental concept of the suggested system revolves around the integration of a series of profound characteristics through the use of CNN. Additionally, the consolidation procedures provide a comprehensive depiction of the classification information. The proposed structure is illustrated in Fig. 1, and the performance of the suggested approach is validated using an FMRI dataset. The dataset includes samples of individuals with ADHD and individuals without ADHD. Fig. 2 shows cases for infected and normal people.

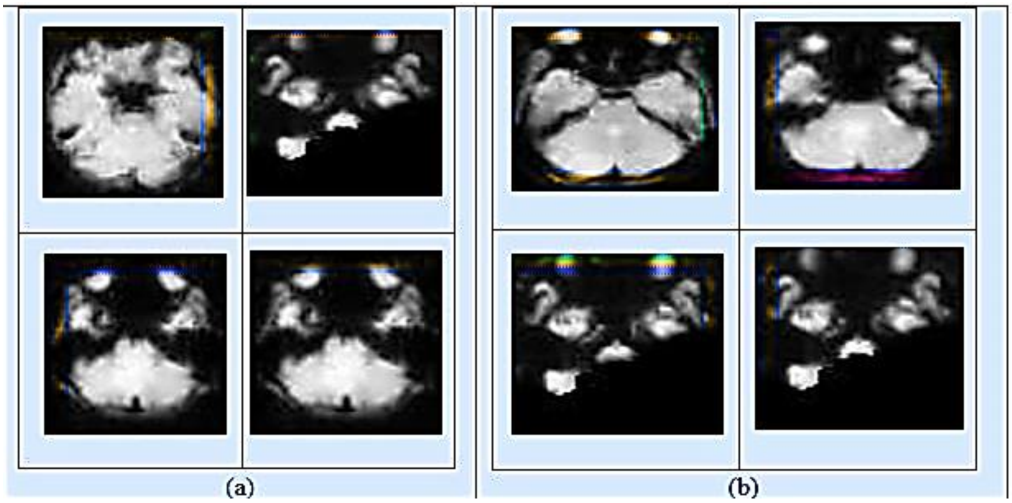

Fig. 2. The dataset for ADHD and the dataset for individuals without ADHD.

The upcoming paper will introduce a CNN architecture composed of 26 layers. As depicted in Figure 1, the first layer is labeled as conv_1, the second as conv_2, and this naming convention continues for the remaining layers. Each layer in this multi-layered structure is responsible for particular tasks, leading to precise classification and effective feature extraction from the images.

III. Experimental Findings

This portion details the evaluation of the upgraded CNN ADHD detection pathway. In a previous study [36], FMRI was utilized in conjunction with CNN to analyze images for the presence of injuries. This concept was visually represented in Fig. 3, which showcased the utilization of 32 filters in the initial convolutional layer. Furthermore, the effectiveness of the enhanced system is gauged based on some metrics. In order to enhance the outcomes and achieve optimal CNN performance.

III.1. Processing of Data

The current study utilizes the ADHD-200 dataset [37],[38], which contains FMRI scans of individuals diagnosed with ADHD. The dataset consists of 2000 entries, which are split into a training set with 70% and a testing set with 30%. Table I displays the distribution of the dataset.

The FMRI dataset in Table I is well-balanced, with 700 samples each from individuals with ADHD and normal subjects in the training set, totaling 1400 samples. This balance ensures that the model learns to differentiate ADHD-related brain activity from normal brain activity without bias. In the testing set, there are 300 samples from ADHD patients and 300 from normal individuals, making up 600 samples. This separation of training and testing data allows for unbiased performance evaluation, ensuring the model's ability to generalize well to unseen data. The dataset's balanced structure contributes to fair and reliable model training and evaluation, enabling accurate performance assessments.

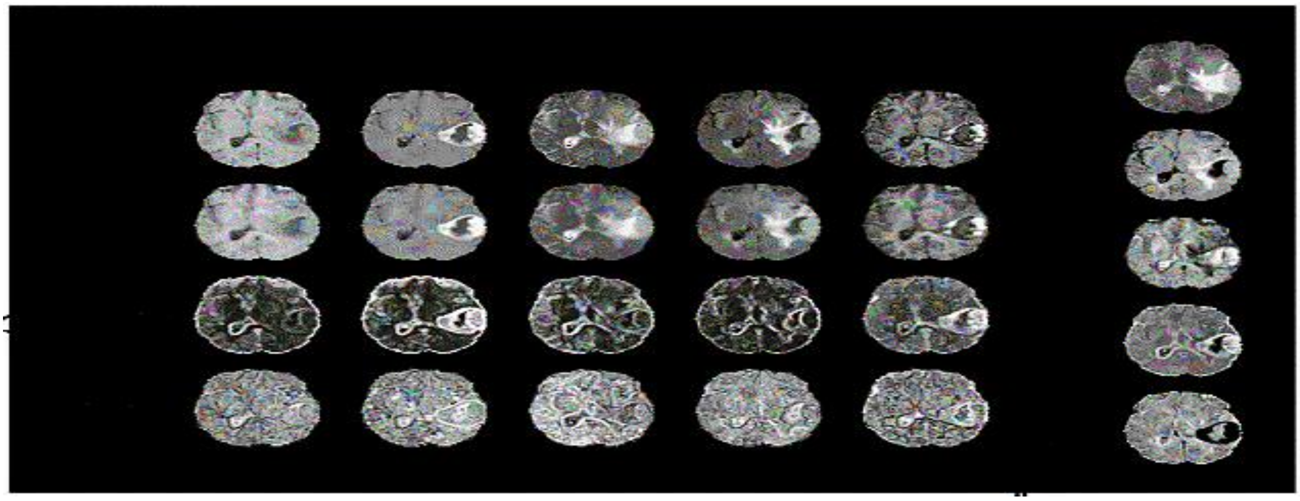

Fig. 3. Extract features from the first convolutional layer using 32 channels.

TABLE I
FMRI DATASET

Dataset	ADHD	Normal	Total
Testing dataset	300	300	600
Training dataset	700	700	1400

III.2. Result Discussions

The proposed CNN utilized three different optimization algorithms. AdaMax, Nadam, and RMS prop. An evaluation was carried out to compare their performance. The results for AdaMax can be found in Table II, showing the relationship between epochs and percentages (%). The ideal parameters for AdaMax were identified at epoch 70, while for Nadam and RMS prop, they were presented in Table III and Table IV, respectively. Table V indicates that RMS prop emerged as the top optimizer.

Table II demonstrates the performance of the CNN on the FMRI dataset using the AdaMax optimization technique. As the number of epochs increases, the model's accuracy improves significantly, starting from 89.72% at 10 epochs to reaching 96.67% at 70 epochs. The precision shows a high consistency, peaking at 96.55% at 80 epochs, indicating that the model is effective in identifying ADHD cases without much false positive rate. Recall steadily increases, reaching a high value of 99.44% at 50 epochs, showcasing the model's ability to correctly identify most ADHD instances. F-score, a combination of precision and recall, also improves with epoch progression, hitting its highest at 96.69% at 70 epochs. These results reflect the positive impact of AdaMax optimization in improving the overall performance of the CNN model on the FMRI dataset, providing a robust and accurate classification model for ADHD diagnosis.

TABLE II
THE UTILIZATION OF THE CNN ON THE FMRI DATASET WITH THE AdaMax OPTIMIZATION TECHNIQUE.

Epochs values	*Accuracy*	*Precision*	*Recall*	*Fscore*
10	89.72	98.64	80.56	88.69
20	91.67	88.27	96.11	92.02
30	91.94	86.83	98.89	92.47
40	94.94	97.62	91.11	94.25
50	95	91.33	99.44	95.21
60	96.11	95.60	96.67	96.13
70	96.67	96.15	97.22	96.69
80	95	96.55	93.33	94.92

Table III presents the performance of the proposed solution using the Nadam optimization algorithm to train the CNN on the FMRI dataset. As the number of epochs increases, the model’s accuracy improves, starting from 83.89% at 10 epochs and reaching 95% at 60 epochs. Precision shows a steady improvement, peaking at 93.79% at 50 epochs, indicating that the model is effectively minimizing false positives. Recall also improves significantly, reaching 96.67% at 60 epochs, highlighting the model's ability to correctly identify most ADHD cases. The F-score follows a similar trend, increasing from 81.65% at 10 epochs to 95.08% at 60 epochs, reflecting a good balance between precision and recall. Overall, the Nadam optimization algorithm proves effective in enhancing the CNN model’s performance, resulting in robust accuracy and reliability for ADHD classification.

TABLE III
THE FMRI DATASET IS UTILIZED IN THE PROPOSED SOLUTION WITH THE NADAM OPTIMIZATION ALGORITHM TO TRAIN THE CNN.

Epochs values	*Accuracy*	*Precision*	*Recall*	*Fscore*
10	83.89	94.85	71.67	81.65
20	87.78	81.48	97.78	88.89
30	90.56	84.43	99.44	91.33
40	91.94	89.12	95.56	92.23
50	93.06	93.79	92.22	92.997
60	95	93.55	96.67	95.08
70	95.83	92.75	99.44	95.99
80	94.72	91.71	98.33	94.91

Table IV shows the performance of the suggested approach, which uses the CNN with the RMSProp optimization algorithm on the FMRI dataset. The accuracy improves steadily from 86.35% at 10 epochs to a peak of 98.33% at 70 epochs, demonstrating significant learning over time. Precision reaches its highest value of 98.33% at 70 epochs, indicating the model is proficient in minimizing false positives. Recall also sees significant improvement, reaching 98.33% at 70 epochs, showing the model's high sensitivity in identifying ADHD cases. The F-score follows a similar trend, peaking at 98.33% at 70 epochs, which reflects an excellent balance between precision and recall. Although the accuracy slightly decreases to 95.62% at 80 epochs, the overall performance demonstrates that the RMSProp algorithm is highly effective in training the CNN, achieving robust classification results for ADHD detection.

TABLE IV
THE SUGGESTED APPROACH INVOLVES UTILIZATION THE CNN ON THE FMRI DATASET USING THE RMS PROP OPTIMIZATION ALGORITHM.

Epochs values	*Accuracy*	*Precision*	*Recall*	*Fscore*
10	86.35	88.56	83.11	88.16
20	88.77	85.98	96.57	91.51
30	90.84	93.78	84.98	88.75
40	92.82	91.51	90.68	90.54
50	93.44	95.77	91.88	94.33
60	95.56	95.76	95.77	95.67
70	98.33	98.33	98.33	98.33
80	95.62	94.02	96.11	95.05

Table V compares the results of three optimization techniques—AdaMax, Nadam, and the proposed RMS—on the CNN model using the FMRI dataset. The RMS optimization technique outperforms the others, achieving the highest accuracy, precision, recall, and F-score, all at 98.33%. This suggests that the RMS algorithm offers superior model performance across all metrics, providing a robust and balanced approach for ADHD detection. In comparison, AdaMax and Nadam show slightly lower results, with AdaMax achieving 96.67% accuracy, 96.15% precision, and 97.22% recall, and Nadam reaching 95.83% accuracy with 99.44% recall. However, the RMS optimization method delivers the best overall performance, highlighting its effectiveness in optimizing the CNN for accurate ADHD diagnosis.

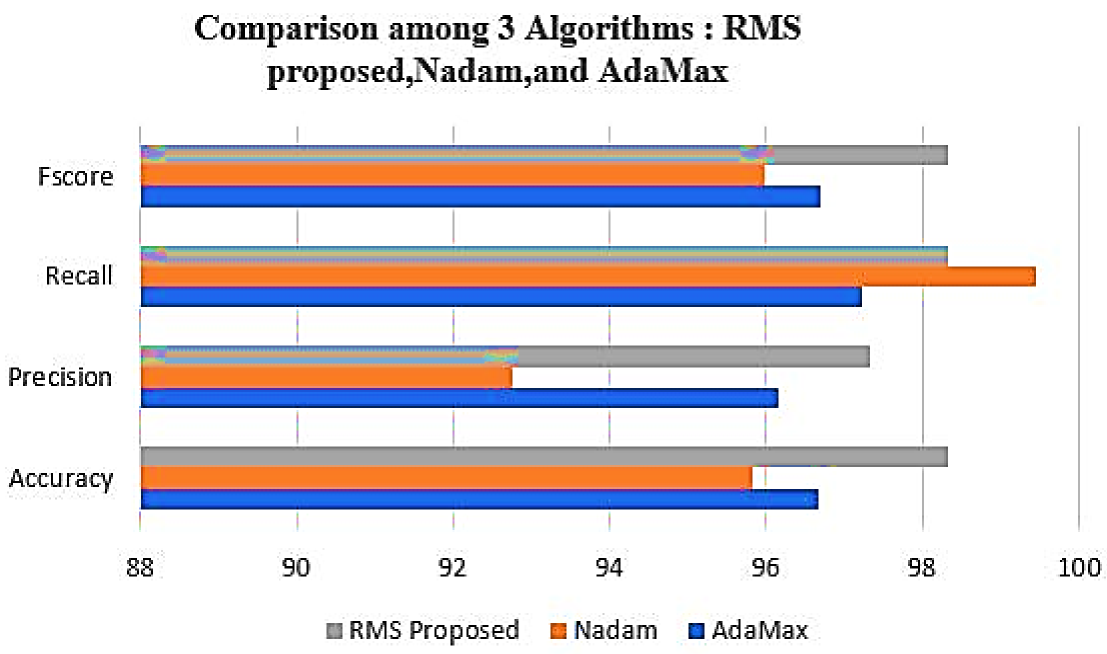

Fig. 4. Depicts a comparison of the optimal results obtained by the three algorithms.

TABLE V
AN ANALSIS OF THE SUPERIOR OUTCOMES ACHIEVED THROUGH THREE OPTIMIZATION TECHNIQUES: AdaMax, NADAM, AND THE SUGGESTED RMS .

Optimization	*Accuracy*	*Precision*	*Recall*	*Fscore*
AdaMax	96.67	96.15	97.22	96.69
Nadam	95.83	92.75	99.44	95.98
RMS Proposed	98.33	98.33	98.33	98.33

The results can be illustrated in Fig. 4, demonstrating that the RMS proposed algorithm yields superior accuracy and performance compared to others. This improvement enhances diagnostic precision and maximizes system performance, ultimately facilitating more effective treatment for the disorder.

Table VI presents a comparative analysis of the performance between two pre-trained models, GoogleNet and ResNet, alongside the proposed CNN model with RMS optimization. The results show that the proposed CNN achieves superior performance, with all metrics—accuracy, precision, recall, and F-score—at 98.33%, significantly outperforming GoogleNet and ResNet. GoogleNet achieved an accuracy of 93.55%, precision of 89.74%, recall of 97.13%, and an F-score of 93.25%, while ResNet performed better than GoogleNet with 95.83% accuracy, 94.92% precision, 96.55% recall, and 95.73% F-score. However, the proposed CNN model outshines both pre-trained models, demonstrating its higher accuracy, precision, recall, and a perfectly balanced F-score, indicating that the proposed approach provides the most effective solution for ADHD diagnosis.

TABLE VI
THE TWO PRE-TRAINED MODELS, NAMELY GOOGLENET, RESNET, AND THE PROPOSED CNN, WERE SUBJECTED TO A COMPARITIVE ANALYSIS.

Network	*Accuracy*	*Precision*	*Recall*	*F-score*
GoogleNet	93.55	89.74	97.13	93.25
ResNet	95.83	94.92	96.55	95.73
Rms proposed	98.33	98.33	98.33	98.33

Fig. 5 displays the accuracy-epoch relationship for Test GoogleNet, ResNet, and the proposed CNN model. Furthermore, Fig. 6 showcases the loss-epoch correlation. The proposed CNN model demonstrates the least loss among the models, highlighting its effectiveness in minimizing loss. The primary focus during training is to decrease the loss value. Unlike accuracy, which is typically used in classification tasks, loss can be applied in both classification and regression problems.

This difference makes loss a more versatile metric, offering deeper insight into model optimization. A lower loss signifies better predictions, indicating that the model is effectively capturing the underlying data patterns. The proposed CNN model's ability to achieve a lower loss across epochs underscores its superior learning capability and robustness compared to GoogleNet and ResNet, which may have plateaued or shown higher variance during training. This result further emphasizes the efficiency of the proposed architecture in balancing performance metrics and achieving reliable outcomes.

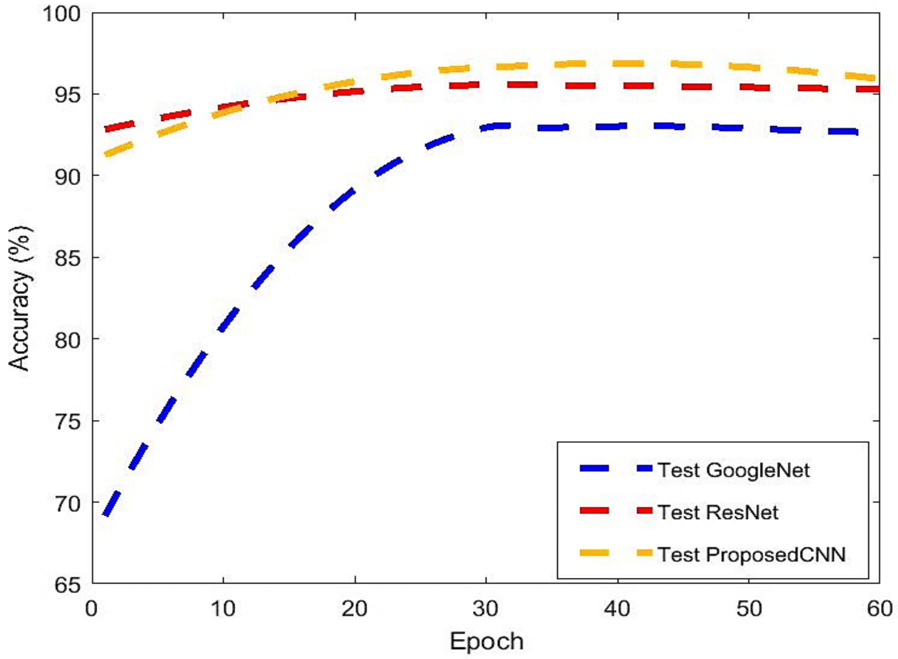

Fig. 5. The correlation between accuracy and the number of iterations across various epochs was examined for the testing of GoogleNet, ResNet, and the proposed CNN model.

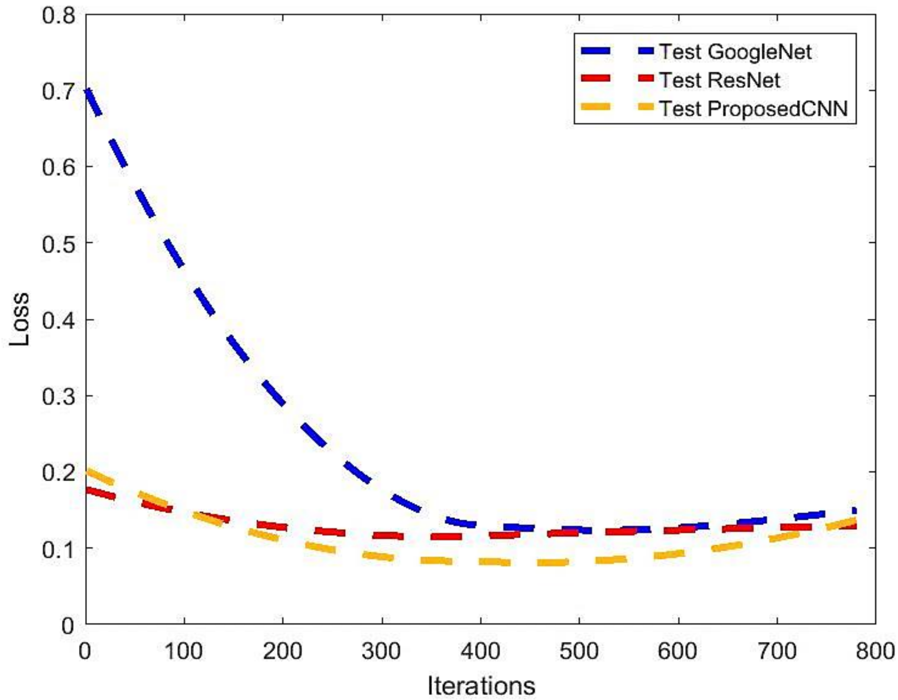

Fig. 6. The correlation between loss and the number of iterations varies across different epochs for the evaluation of GoogleNet, ResNet, and the proposed CNN model.

The confusion matrix is utilized as a means to assess the efficiency of artificial intelligence classification. Figs. 7, 8, and 9 depict the confusion between the categories "yes" and "no". The dataset consists of 600 images for ADHD and 600 images for normal cases. Fig. 10 presents a comparison between the two.

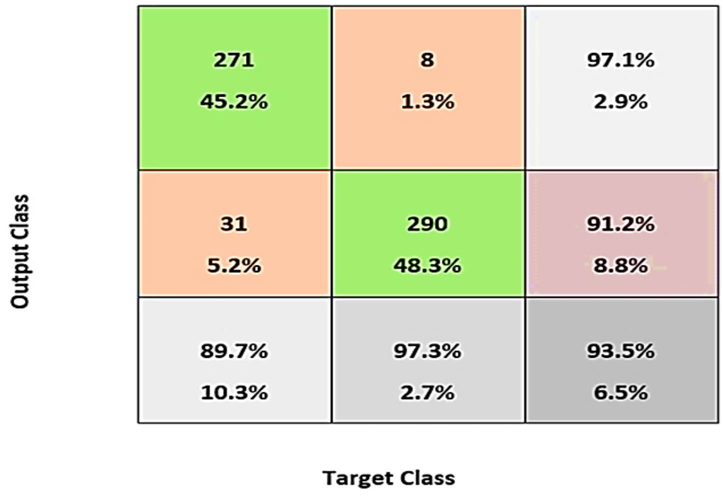

Fig. 7. GoogleNet confusion matrix

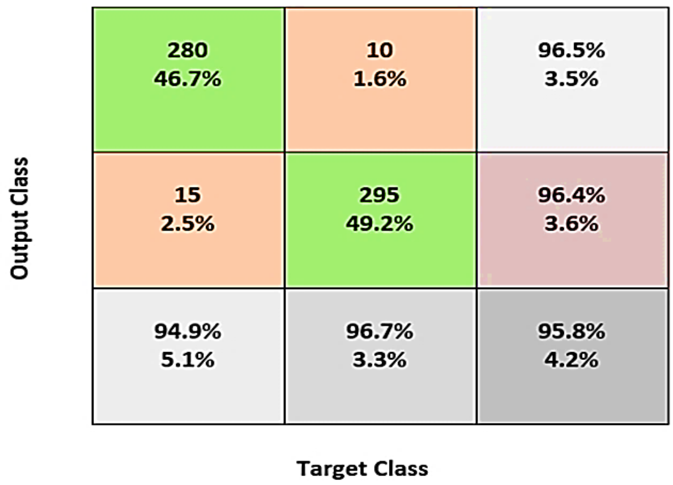

Fig. 8. ResNet confusion matrix

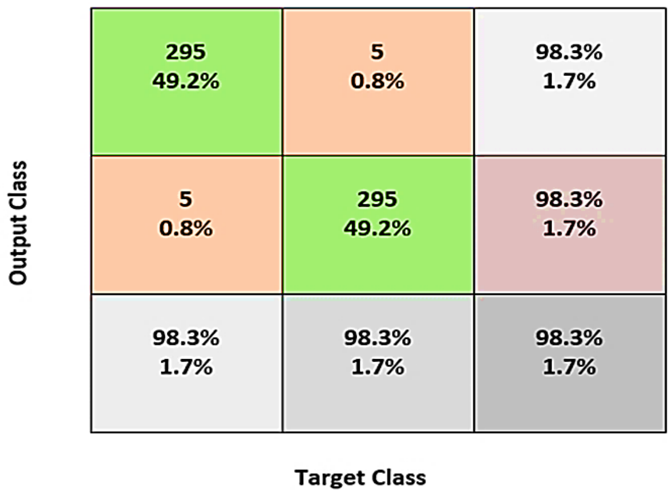

Fig. 9. The proposed CNN confusion matrix

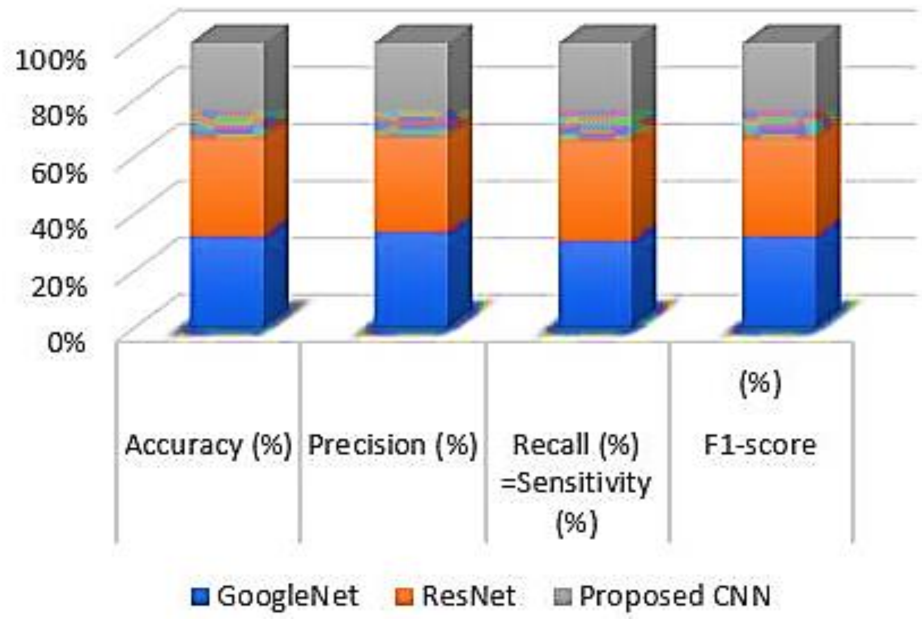

Fig. 10. The performance outcomes of the suggested GoogleNet, ResNet, and CNN models were evaluated using a 70/30 training/test ratio.

The ROC diagrams displayed in Fig.11 confirm the impressive performance of the fusion system being proposed. Moreover, the AUC provides a holistic measure of performance across all possible classification thresholds. Specifically, the AUC values are 0.99512 for ResNet18, 0.99404 for GoogleNet, and 0.99754 for the CNN model under consideration.

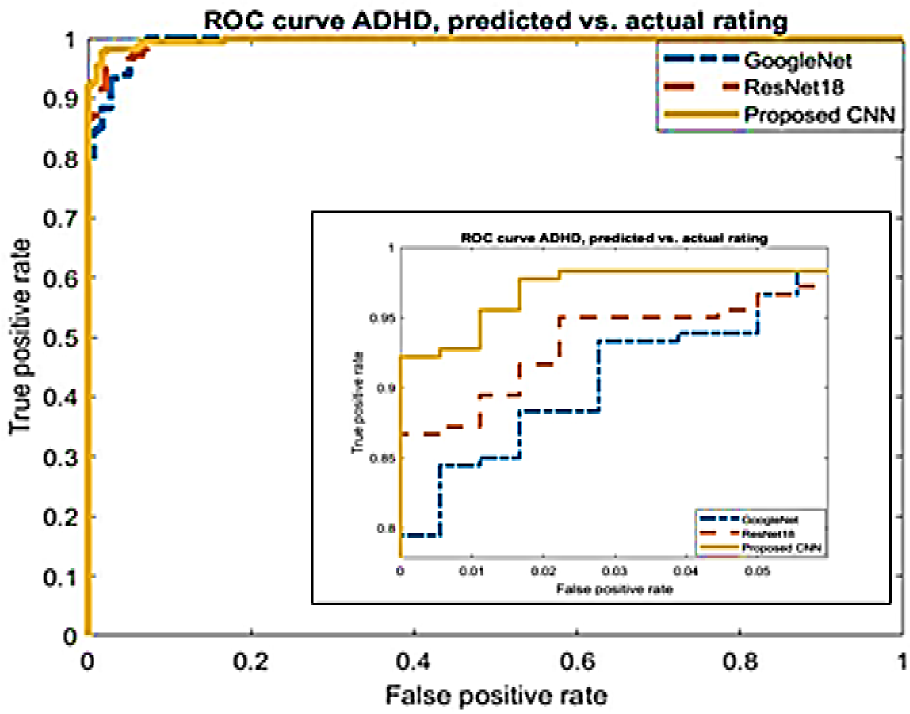

Fig. 11. The ROC curve's rate (TP vs. FP) varies across different classification thresholds.

IV. Conclusion and Future Work

In conclusion, the detection and classification of ADHD were successfully achieved by utilizing fMRI with optical amplification. Given that the fMRI signal weakens as it travels toward the receiver, optical amplification is employed to mitigate this loss, ensuring better signal clarity for diagnosis. A carefully curated dataset of images was used for training, providing a robust foundation for detecting ADHD. Convolutional Neural Networks, known for their accuracy in image classification and feature extraction, were employed to enhance the system's ability to recognize important characteristics indicative of ADHD. The proposed model, utilizing CNNs, outperformed existing methods, achieving an impressive accuracy of 98.33%. This result highlights the effectiveness of combining fMRI with optical amplification in ADHD detection. Moreover, our study demonstrated how critical parameters, including image quality and optimization techniques, contribute to improving diagnostic accuracy, thus providing a powerful tool for early and reliable ADHD diagnosis.

Future work in advancing ADHD diagnosis using fMRI and CNNs can focus on several key areas to further improve accuracy and system efficiency. One potential direction is to expand the dataset by incorporating a more diverse range of ADHD cases, including varying age groups, genders, and comorbidities, to ensure that the model generalizes well across different populations. Additionally, exploring other deep learning architectures, such as Generative Adversarial Networks (GANs) or attention-based models, may provide further enhancement in feature extraction and classification accuracy. Further optimization of the proposed methods, including experimenting with additional advanced optimization algorithms and fine-tuning hyperparameters, could help improve the model's robustness and reduce the risk of overfitting. Additionally, incorporating multimodal data sources, such as behavioral and genetic information, alongside fMRI images, might allow for a more comprehensive and holistic diagnostic approach. The integration of real-time diagnostic tools into clinical practice is another avenue for future development, enabling timely intervention and more personalized treatment strategies for ADHD. Lastly, collaboration with healthcare professionals to validate the system's clinical applicability and ensuring it meets regulatory standards for medical usage would be crucial for translating this research into a practical solution for early ADHD diagnosis.

Declarations

Funding
The authors received no financial support for the research, authorship, and/or publication of this article.

Author Contributions
The authors declare that the study was conducted in collaboration with each other with equal responsibility. The manuscript was read and approved by all authors.

Conflict of interest
The authors declare no conflict of interest.

Data Availability Statement
The data that support the findings of this study are available upon reasonable request.

Competing Interests
The authors have no relevant financial or non- financial interests to disclose

References

[1] Bellec, P., Chu, C., Chouinard-Decorte, F., Benhajali, Y., Margulies, D. S., & Craddock, R. C. The neuro bureau ADHD-200 preprocessed repository. *Neuroimage*, *144*, 275-286 (2017)

[2] Polanczyk, G. V., Willcutt, E. G., Salum, G. A., Kieling, C., and Rohde, L. A. ADHD prevalence estimates across three decades: an updated systematic review and meta-regression analysis. *International journal of epidemiology*, *43*(2), 434-442 (2014)

[3] Dey, S., Rao, A. R., and Shah, M. Attributed graph distance measure for automatic detection of attention deficit hyperactive disordered subjects. *Frontiers in neural circuits*, *8*, 64 (2014)

[4] Chang, C. W., Ho, C. C., and Chen, J. H. ADHD classification by a texture analysis of anatomical brain MRI data. *Frontiers in systems neuroscience, 6,* 66 (2012)

[5] Qiu, M. G., Ye, Z., Li, Q. Y., Liu, G. J., Xie, B., and Wang, J. Changes of brain structure and function in ADHD children. *Brain topography, 24,* 243-252 (2011)

[6] Danielson, M. L., Holbrook, J. R., Bitsko, R. H., Newsome, K., Charania, S. N., McCord, R. F., ... and Blumberg, S. J. State-level estimates of the prevalence of parent-reported ADHD diagnosis and treatment among US children and adolescents, 2016 to 2019. *Journal of attention disorders, 26*(13), 1685-1697 (2022)

[7] Zou, L., Zheng, J., Miao, C., Mckeown, M. J., and Wang, Z. J. 3D CNN based automatic diagnosis of attention deficit hyperactivity disorder using functional and structural MRI. *Ieee Access, 5*, 23626-23636 (2017)

[8] Dimond, D., Perry, R., Iaria, G., and Bray, S. Visuospatial short-term memory and dorsal visual gray matter volume. *Cortex*, *113*, 184-190 (2019)

[9] Kuang, D., Guo, X., an, X., Zhao, Y., and He, L. Discrimination of ADHD based on FMRI data with deep belief network. In Intelligent Computing in Bioinformatics: *10th International Conference, ICIC 2014, Taiyuan, China*, August 3-6, 2014. Proceedings 10 (pp. 225-232). Springer International Publishing (2014)

[10] Peng, X., Lin, P., Zhang, T., and Wang, J. Extreme learning machine-based classification of ADHD using brain structural MRI data. *PloS one, 8*(11), e79476 (2013)

[11] Johnston, B. A., Mwangi, B., Matthews, K., Coghill, D., Konrad, K., and Steele, J. D. Brainstem abnormalities in attention deficit hyperactivity disorder support high accuracy individual diagnostic classification. *Human brain mapping, 35*(10), 5179-5189m (2014)

[12] Faraone, S. V., Banaschewski, T., Coghill, D., Zheng, Y., Biederman, J., Bellgrove, M. A., and Wang, Y. The world federation of ADHD international consensus statement: 208 evidence-based conclusions about the disorder. *Neuroscience & biobehavioral reviews*, *128*, 789-818 (2021)

[13] Dolz, J., Desrosiers, C., and Ayed, I. B. 3D fully convolutional networks for subcortical segmentation in MRI: A large-scale study. *NeuroImage, 170*, 456-470 (2018)

[14] Sarraf, S., and Tofighi, G. Deep learning-based pipeline to recognize Alzheimer's disease using FMRI data. In *2016 future technologies conference (FTC)* (pp. 816-820). IEEE (2016, December)

[15] Szegedy, C., Ioffe, S., Vanhoucke, V., and Alemi, A. Inception-v4, inception-resnet and the impact of residual connections on learning. *In Proceedings of the AAAI conference on artificial intelligence,* Vol. 31, No. 1 (2017, February)

[16] Yang, C., Rangarajan, A., and Ranka, S. Visual explanations from deep 3D convolutional neural networks for Alzheimer's disease classification. *In AMIA annual symposium proceedings* (Vol. 2018, p. 1571). American Medical Informatics Association (2018)

[17] Kamnitsas, K., Ledig, C., Newcombe, V. F., Simpson, J. P., Kane, A. D., Menon, D. K., ... and Glocker, B. Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. *Medical image analysis, 36*, 61-78 (2017)

[18] Minz, A., and Mahobiya, C. MR Image classification using adaboost for brain tumor type. In 2017 *IEEE 7th International Advance Computing Conference (IACC)* (pp. 701-705). IEEE (2017, January)

[19] Deepak, S., and Ameer, P. M. Brain tumor classification using deep CNN features via transfer learning. *Computers in biology and medicine, 111*, 103345 (2019)

[20] Zeng, G., He, Y., Yu, Z., Yang, X., Yang, R., and Zhang, L. Preparation of novel high copper ions removal membranes by embedding organosilane-functionalized multi-walled carbon nanotube. *Journal of Chemical Technology & Biotechnology, 91*(8), 2322-2330 (2016)

[21] Raju, A. R., Suresh, P., and Rao, R. R. Bayesian HCS-based multi-SVNN: a classification approach for brain tumor segmentation and classification using Bayesian fuzzy clustering. *Biocybernetics and Biomedical Engineering, 38*(3), 646-660 (2018)

[22] Sert, E., Özyurt, F., and Doğantekin, A. A new approach for brain tumor diagnosis system: single image super resolution based maximum fuzzy entropy segmentation and convolutional neural network. *Medical hypotheses*, *133*, 109413 (2019)

[23] Das, S. CNN Architectures: LeNet, AlexNet, VGG, GoogLeNet, ResNet and more…. *Medium*, (November 16), (2017)

[24] Huang, G., Liu, Z., Van Der Maaten, L., and Weinberger, K. Q. densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4700-4708), (2017)

[25] Chollet, F. Xception: Deep learning with depthwise separable convolutions. *In Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1251-1258), (2017)

[26] Kaiming He; Xiangyu Zhang; Shaoqing Ren; Jian Sun, et.al "Deep Residual Learning for Image Recognition", *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, (pp. 770-778), (June 2016)

[27] Angriman, M., Beggiato, A., & Cortese, S. Anatomical and functional brain imaging in childhood ADHD: update 2013. *Current Developmental Disorders Reports*, *1*, 29-40 (2014)

[28] Dai, D., Wang, J., Hua, J., & He, H. Classification of ADHD children through multimodal magnetic resonance imaging. *Frontiers in systems neuroscience*, *6*, 63 (2012)

[29] Guo, X., an, X., Kuang, D., Zhao, Y., & He, L. ADHD-200 classification based on social network method. *In Intelligent Computing in Bioinformatics: 10th International Conference, ICIC 2014, Taiyuan, China*, August 3-6, 2014. Proceedings 10 (pp. 233-240). Springer International Publishing (2014)

[30] Salah, E., Shokair, M., El-Samie, F. E. A., & Shalaby, W. A. Utilization of FMRI with optical amplification to diagnose attention deficit hyperactivity disorder. *Journal of Optics*, 1-12 (2024)

[31] Simonsen, A., Sánchez-Heredia, J. D., Saarinen, S. A., Ardenkjær-Larsen, J. H., Schliesser, A., and Polzik, E. S. Magnetic resonance imaging with optical preamplification and detection. *Scientific reports*, *9*(1), 18173 (2019)

[32] Loh, H. W., Ooi, C. P., Barua, P. D., Palmer, E. E., Molinari, F., and Acharya, U. R. Automated detection of ADHD: Current trends and future perspective. *Computers in Biology and Medicine, 146*, 105525 (2022)

[33] Peng, X., Lin, P., Zhang, T., & Wang, J. Extreme learning machine-based classification of ADHD using brain structural MRI data. *PloS one, 8*(11), e79476 (2013)

[34] Takeda, T., Stotesbery, K., Power, T., Ambrosini, P. J., Berrettini, W., Hakonarson, H., and Elia, J. Parental ADHD status and its association with proband ADHD subtype and severity. *The Journal of pediatrics, 157*(6), 995-1000 (2010)

[35] Mao, Z., Su, Y., Xu, G., Wang, X., Huang, Y., Yue, W., ... and Xiong, N. Spatio-temporal deep learning method for adhd fmri classification. *Information Sciences, 499*, 1-11(2019)

[36] Murphy, K., & Fox, M. D. Towards a consensus regarding global signal regression for resting state functional connectivity MRI. *Neuroimage, 154*, 169-173. (2017)
[37] ADHD-200 consortium. The ADHD-200 consortium: a model to advance the translational potential of neuroimaging in clinical neuroscience. *Frontiers in systems neuroscience*, *6*, 62 (2012)
[38] Salah, E., Shokair, M., Ismail, H. M., Shalaby, W. A., Elkorany, A., & Zayed, M. M. ADHD classification using convolution neural network. *International Journal of Engineering and Applied Science*, *October 6 University,1*(1), (2024), http://doi.org/10.21608/ijeasou.2024.374365