# Knowledge Distillation for ADHD

Subjects: Computer Science, Artificial Intelligence

Contributor: Naseer Ahmed Khan

Attention Deficit Hyperactivity Disorder (ADHD) is a brain disorder with characteristics such as lack of concentration, excessive fidgeting, outbursts of emotions, lack of patience, difficulty in organizing tasks, increased forgetfulness, and interrupting conversation, and it is affecting millions of people worldwide.

ADHD autoencoder classification connectivity

## 1. Introduction

Brain is considered the most intricate and mysterious organ in the human body with complexity in networks in the spatial as well the temporal domain. Brain's functional and physical levels consists of five major regions: Frontal, Occipital, Parietal, Subcortical, and Temporal regions [1]. The complexity of the human brain is related to both the increasing age and difficulty level of the computational task. Increasing age of the person and the complicated nature of the task make it difficult for the brain to make decisions [2][3]. The volume of data generated by the human brain is huge and this amount of data in just half a minute is equivalent to the data generated by the Hubble telescope in its entire life [4], which makes analysis based on human brain data a challenging task.

Attention Deficit Hyperactivity Disorder (ADHD) is a brain disorder that is characterized with persistent lack of attention, high impulsiveness, restlessness, and hyperactivity with numerous environmental, neurological, and genetic factors [5][6][7]. The rate of ADHD diagnosis is increasing in children and it affects 8% to 12% of the world's child population as indicated in the studies in [8][9]. A benchmark for the prevalence of ADHD among children using meta-analysis based on 179 estimates of the prevalence in 175 studies is proposed in [10]. There are both genetic- [11] and neurological-related [12] interpretations of the cause of ADHD, specifically, genes LPHN3 and CDH13 and damage to the frontal lobe, respectively.

ADHD on the subjects is measured using a variety of modalities with each modality has peculiar characteristics. These modalities include DTI (Diffusion Tensor Imaging), EEG (Electroencephalography), fMRI (Functional Magnetic Resonance Imaging), PET (Positron Emission Tomography), and SPECT (Single Photon Emission Computed Tomography). Brain structural alterations were observed in proband, alterations in brain functional connectivity and influence of the drug in the treatment of ADHD using the DTI modality were discussed in the studies in [12][13][14]. Diagnostic psychiatry tests for ADHD were based on four steps using the the 17 meta-studies and a meta-analysis based on randomized control trials on the ADHD were discussed in [15][16], respectively. A triple-blinded studies on the 275 children and adolescents to integrate the biomarkers for the diagnosis of ADHD and a deep learning-based framework for the diagnosis of ADHD were discussed in [17][18]. A convolution neural network and a comparisons of alpha powers between the 25 patients and 22 healthy controls for the diagnosis of ADHD using the EEG modality were discussed in [19][20][21], respectively. Effect of psychostimulants on the 16 youths, with modeling of the brain using the resting state of the brain with the help of Independent Component Analysis (ICA) and A meta-analysis of 55 studies involving 55 children and adults were discussed in [22][23][24], respectively. The inter-connections and intra-connections in the brain functional regions, effect of 40 mg methylphenidate on the 37 individuals, and effect of L-theanine (2.5 mg) and caffeine (2.0 mg) on the patients with ADHD using fMRI modality were studied in [25][26][27], respectively. PET-related studies have also shown promising results on the ADHD subjects and the biology of this disorder [28]. A significant increase in Dopamine Transporter (DAT) binding was observed in [29] conducted on 47 subjects with matched control. In [30], alterations in the cortical thickness were found between the ADHD and the healthy controls. One multimodal study [31] using PET and genetic data on the 20 ADHD and matched healthy controls and another machine learning-based study [32] on 16 ADHD subjects and 22 healthy controls found promising results in the diagnosis of this disorder. SPECT-based studies were conducted in [33] to distinguish sub-types of ADHD. A meta-analysis [34] involving 51 studies on 53 ADHD subjects found 13 promising genes for the diagnosis of ADHD using the SPECT-based image scans on the patients. A study on ADHD and other disorders using the SPECT modality showed alterations in some of the brain regions [35]. A genetic SPECT study [36] found a decrease in DAT on the 20 adolescents. A use of SPECT as to how it is aiding the medical treatment of the ADHD subject is discussed in the study [37].

fMRI studies based on functional connectivity on the ADHD are becoming, of late, very popular due the the noninvasive nature of fMRI and interpretable regions found from the extraction of functional connectivity matrix. In this regard, ADHD diagnosis using personal characteristics (age, IQ, and handedness) [38] showed promising results. Independent Component Analysis (ICA) with the combination of functional connectivity matrix found neural network dysregulation in ADHD [39]. Fusion [40] of non-imaging data with the imaging data also showed promising results in the study. fMRI study also found functional connectivity alterations [41] in the right inferior frontal cortex of the adolescents. A study using Convolution Neural Network (CNN) [42] on the multi-site resting state fMRI data showed promising results in the classification of the ADHD.

## 2. Structural Information Based Approaches

In [43], the authors used morphological information to classify 210 ADHD subjects from the 226 healthy controls. They used isotropic local binary patterns on three orthogonal planes to extract features from the high-resolution MRI scan data on the subjects resulting in 69% accuracy. In the study [44], high-resolution 3-D scans of 55 ADHD subjects and matched healthy controls were acquired using MRI machine. After processing them with the FreeSurfer [45] software, 340 features such as cortical thickness, curvature, volume, etc. were measured for each type of subjects resulting in maximum accuracy of 90.18% when given to Extreme Learning Machine classifier. Gaussian Process Classification was applied in [46] to the brain gray matter volumetric data including 29 ADHD and matched control subjects resulting in overall accuracy of 79.3%. Structural as well as functional features were used in [47][48] to classify the ADHD subjects resulting in 76% accuracy in the multi-class setting and 92.8% accuracy in the binary class setting in the first study and 67% accuracy in the second study. A study [49] on 508 individuals containing ADHD subjects and healthy control using the source based morphometry of the brain scans showed alterations in bilateral CrusI and bilateral insula between the two conditions among subjects.

## 3. Functional Connectivity Based Approaches

In [50], decreased functional connectivity was observed in dorsal anterior cingulate cortex and regions of default mode network between the 21 ADHD patients and 21 matched healthy controls. In study [51], 20 medication-naive ADHD children with 20 age- and gender-matched healthy controls were investigated for the alterations in functional connectivity and found delayed maturation in two functional networks. In [52], functional connectivity alterations in the brain areas related to motor circuitry which contribute to the functioning of motor and attention were exhibited in children. A Fully Connected Cascade (FCC) neural network was proposed in [53] to discriminate ADHD from the healthy controls, and directional and non-directional based connectivity features were given to the classifier resulting in 90% accuracy. In [54], involving 20 ADHD patients and 27 healthy controls, increased connectivity in the brain Default Model Network (DMN) was found both between and among the functional connectivity networks. In [55], from the data on 95 ADHD subjects and 90 healthy controls, the authors selected five subcortical regions. Their analysis showed significant difference in resting state functional connectivity in caudate nucleus. In [56], the authors formed two cohorts: a child cohort consisting of 34 ADHD and 28 health controls and an adult cohort consisting of 112 ADHD and 77 healthy controls. Functional connectivity alterations were found both in the children cohort and in the adult cohort. A multi-objective scheme using Support Vector Machine (SVM) was used in [57] to first tackle the task of imbalanced dataset and then classifying the ADHD subjects from the healthy controls with promising results. The dual subspace method was observed in [58] by first making two subspaces corresponding to ADHD and healthy control and then using them based on the energy principle to classify ADHD from the healthy controls.

## 4. Deep Learning-Based Approaches

Deep learning is a computational model using which we learn multilevel abstraction of the input data and learn the intricate pattern from the data by training layer wise feed forward neural network with back-propagation algorithm [59]. Deep learning is closely associated to machine learning which has applications in various practical domains such as IoT, renewable energy, medicine, and agriculture [60][61][62][63]. Of late, deep learning is being used increasingly more in the medical image analysis domain to replace handcrafted features with automatic extracted features [64][65]. In [66], the authors discussed scenarios where the subdomains of deep learning including computer vision, natural language processing and reinforcement learning can be applied in the healthcare setups. A 4D-CNN-based algorithm was proposed in [67] with data augmentation for balancing to extract both spatial and temporal features from the ADHD subjects and healthy controls resulting in 71.3% accuracy. DeepFMRI was proposed in [68], three networks—a feature extractor network, a functional connectivity network, and a classification network—were all combined into one big network to form an End-To-End approach with promising results across three ADHD sites. In [69], a Convolution Denoising Autoencoder (CDAE) was used to extract the discriminating features between the ADHD subjects and healthy control and then the Adaptive boosting Decision Trees (AdaDt) was used for classification using the extracted Features.

## References


1. Bassett, D.S.; Gazzaniga, M.S. Understanding complexity in the human brain. Trends Cogn. Sci. 2011, 15, 200–209.
2. Bossaerts, P.; Murawski, C. Computational complexity and human decision-making. Trends Cogn. Sci. 2017, 21, 917–929.
3. Anokhin, A.P.; Birbaumer, N.; Lutzenberger, W.; Nikolaev, A.; Vogel, F. Age increases brain complexity. Electroencephalogr. Clin. Neurophysiol. 1996, 99, 63–68.
4. Abbott, A. Solving the brain. Nature 2013, 499, 272.
5. Wender, P.H. Attention-deficit hyperactivity disorder in adults. Psychiatr. Clin. N. Am. 1998, 21, 761–774.
6. Swanson, J.M.; Volkow, N.D.; Newcorn, J.; Casey, B.; Moyzis, R.; Grandy, D.; Posner, M. Attention deficit hyperactivity disorder. Encycl. Cogn. Sci. 2006, 45, 642–657.
7. Faraone, S.; Asherson, P.; Banaschewski, T.; Biederman, J.; Buitelaar, J.; Ramos-Quiroga, J.; Franke, B. Attention-deficit/hyperactivity disorder. Nat. Rev. Dis. Prim. 2015, 1, 15020.
8. Doyle, A.E.; Willcutt, E.G.; Seidman, L.J.; Biederman, J.; Chouinard, V.A.; Silva, J.; Faraone, S.V. Attention-deficit/hyperactivity disorder endophenotypes. Biol. Psychiatry 2005, 57, 1324–1335.
9. Bush, G. Attention-deficit/hyperactivity disorder and attention networks. Neuropsychopharmacology 2010, 35, 278–300.
10. Thomas, R.; Sanders, S.; Doust, J.; Beller, E.; Glasziou, P. Prevalence of attention-deficit/hyperactivity disorder: A systematic review and meta-analysis. Pediatrics 2015, 135, e994–e1001.
11. Franke, B.; Faraone, S.; Asherson, P.; Buitelaar, J.; Bau, C.; Ramos-Quiroga, J.A.; Mick, E.; Grevet, E.; Johansson, S.; Haavik, J.; et al. The genetics of attention deficit/hyperactivity disorder in adults, a review. Mol. Psychiatry 2012, 17, 960–987.
12. Chiang, H.L.; Yung-Chin, H.; Chi-Yuan, S.; Tseng, W.Y.I.; Gau, S.S.F. White matter endophenotype candidates for ADHD: A diffusion imaging tractography study with sibling design. Psychol. Med. 2020, 50, 1203–1213.
13. Qiu, M.G.; Ye, Z.; Li, Q.Y.; Liu, G.J.; Xie, B.; Wang, J. Changes of brain structure and function in ADHD children. Brain Topogr. 2011, 24, 243–252.
14. de Luis-García, R.; Cabús-Piñol, G.; Imaz-Roncero, C.; Argibay-Quiñones, D.; Barrio-Arranz, G.; Aja-Fernández, S.; Alberola-López, C. Attention deficit/hyperactivity disorder and medication with

stimulants in young children: A DTI study. Prog. Neuro-Psychopharmacol. Biol. Psychiatry 2015, 57, 176–184.

15. Boutros, N.; Fraenkel, L.; Feingold, A. A four-step approach for developing diagnostic tests in psychiatry: EEG in ADHD as a test case. J. Neuropsychiatry Clin. Neurosci. 2005, 17, 455–464.
16. Micoulaud-Franchi, J.A.; Geoffroy, P.A.; Fond, G.; Lopez, R.; Bioulac, S.; Philip, P. EEG neurofeedback treatments in children with ADHD: An updated meta-analysis of randomized controlled trials. Front. Hum. Neurosci. 2014, 8, 906.
17. Heinrich, H.; Busch, K.; Studer, P.; Erbe, K.; Moll, G.H.; Kratz, O. EEG spectral analysis of attention in ADHD: Implications for neurofeedback training? Front. Hum. Neurosci. 2014, 8, 611.
18. Snyder, S.M.; Rugino, T.A.; Hornig, M.; Stein, M.A. Integration of an EEG biomarker with a clinician's ADHD evaluation. Brain Behav. 2015, 5, e00330.
19. Chen, H.; Song, Y.; Li, X. A deep learning framework for identifying children with ADHD using an EEG-based brain network. Neurocomputing 2019, 356, 83–96.
20. Dubreuil-Vall, L.; Ruffini, G.; Camprodon, J.A. Deep learning convolutional neural networks discriminate adult ADHD from healthy individuals on the basis of event-related spectral EEG. Front. Neurosci. 2020, 14, 251.
21. Deiber, M.P.; Hasler, R.; Colin, J.; Dayer, A.; Aubry, J.M.; Baggio, S.; Perroud, N.; Ros, T. Linking alpha oscillations, attention and inhibitory control in adult ADHD with EEG neurofeedback. NeuroImage Clin. 2020, 25, 102145.
22. Peterson, B.S.; Potenza, M.N.; Wang, Z.; Zhu, H.; Martin, A.; Marsh, R.; Plessen, K.J.; Yu, S. An FMRI study of the effects of psychostimulants on default-mode processing during Stroop task performance in youths with ADHD. Am. J. Psychiatry 2009, 166, 1286–1294.
23. Zuo, X.N. Modeling Resting-State Brain Functional Integration. Nat. Preced. 2010.
24. Cortese, S.; Kelly, C.; Chabernaud, C.; Proal, E.; Di Martino, A.; Milham, M.P.; Castellanos, F.X. Toward systems neuroscience of ADHD: A meta-analysis of 55 fMRI studies. Am. J. Psychiatry 2012, 169, 1038–1055.
25. Kaboodvand, N.; Iravani, B.; Fransson, P. Dynamic synergetic configurations of resting-state networks in ADHD. NeuroImage 2020, 207, 116347.
26. Sweitzer, M.M.; Kollins, S.H.; Kozink, R.V.; Hallyburton, M.; English, J.; Addicott, M.A.; Oliver, J.A.; McClernon, F.J. ADHD, smoking withdrawal, and inhibitory control: Results of a Neuroimaging Study with methylphenidate challenge. Neuropsychopharmacology 2018, 43, 851–858.
27. Kahathuduwa, C.N.; Wakefield, S.; West, B.D.; Blume, J.; Dassanayake, T.L.; Weerasinghe, V.S.; Mastergeorge, A. Effects of l-theanine–caffeine combination on sustained attention and inhibitory

control among children with ADHD: A proof-of-concept neuroimaging RCT. Sci. Rep. 2020, 10, 13072.

28. Zimmer, L. Positron emission tomography neuroimaging for a better understanding of the biology of ADHD. Neuropharmacology 2009, 57, 601–607.
29. Spencer, T.J.; Biederman, J.; Madras, B.K.; Dougherty, D.D.; Bonab, A.A.; Livni, E.; Meltzer, P.C.; Martin, J.; Rauch, S.; Fischman, A.J. Further evidence of dopamine transporter dysregulation in ADHD: A controlled PET imaging study using altropane. Biol. Psychiatry 2007, 62, 1059–1061.
30. Cherkasova, M.V.; Faridi, N.; Casey, K.F.; Larcher, K.; O'Driscoll, G.A.; Hechtman, L.; Joober, R.; Baker, G.B.; Palmer, J.; Evans, A.C.; et al. Differential associations between cortical thickness and striatal dopamine in treatment-naïve adults with ADHD vs. healthy controls. Front. Hum. Neurosci. 2017, 11, 421.
31. Sigurdardottir, H.L.; Kranz, G.S.; Rami-Mark, C.; James, G.M.; Vanicek, T.; Gryglewski, G.; Kautzky, A.; Hienert, M.; Traub-Weidinger, T.; Mitterhauser, M.; et al. Effects of norepinephrine transporter gene variants on NET binding in ADHD and healthy controls investigated by PET. Hum. Brain Mapp. 2016, 37, 884–895.
32. Kautzky, A.; Vanicek, T.; Philippe, C.; Kranz, G.; Wadsak, W.; Mitterhauser, M.; Hartmann, A.; Hahn, A.; Hacker, M.; Rujescu, D.; et al. Machine learning classification of ADHD and HC by multimodal serotonergic data. Transl. Psychiatry 2020, 10, 104.
33. Grodner, K.; Harcourt, S.; Sattuar, Z.; STrong, A.; Golden, C.; Amen, D.; Willeumier, K.; Taylor, D. B-01 Differentiating Attention Deficit/Hyperactivity Disorder (ADHD) Combined Type and ADHD Inattentive Type Using SPECT Imaging. Arch. Clin. Neuropsychol. 2016, 31, 613.
34. Klein, M.; Onnink, M.; van Donkelaar, M.; Wolfers, T.; Harich, B.; Shi, Y.; Dammers, J.; Arias-Vásquez, A.; Hoogman, M.; Franke, B. Brain imaging genetics in ADHD and beyond–mapping pathways from gene to disorder at different levels of complexity. Neurosci. Biobehav. Rev. 2017, 80, 115–155.
35. Karande, S.; Deshmukh, N.; Rangarajan, V.; Agrawal, A.; Sholapurwala, R. Brain SPECT scans in students with specific learning disability: Preliminary results. J. Postgrad. Med. 2019, 65, 33.
36. Akay, A.P.; Kaya, G.C.; Kose, S.; Yazıcıoğlu, Ç.E.; Erkuran, H.Ö.; Güney, S.A.; Oğuz, K.; Keskin, D.; Baykara, B.; Emiroğlu, N.İ.; et al. Genetic imaging study with [Tc-99m] TRODAT-1 SPECT in adolescents with ADHD using OROS-methylphenidate. Prog. Neuro-Psychopharmacol. Biol. Psychiatry 2018, 86, 294–300.
37. Henderson, T.A.; van Lierop, M.J.; McLean, M.; Uszler, J.M.; Thornton, J.F.; Siow, Y.H.; Pavel, D.G.; Cardaci, J.; Cohen, P. Functional Neuroimaging in Psychiatry—Aiding in Diagnosis and Guiding Treatment. What the American Psychiatric Association Does Not Know. Front. Psychiatry 2020, 11, 276.

38. Brown, M.R.; Sidhu, G.S.; Greiner, R.; Asgarian, N.; Bastani, M.; Silverstone, P.H.; Greenshaw, A.J.; Dursun, S.M. ADHD-200 Global Competition: Diagnosing ADHD using personal characteristic data can outperform resting state fMRI measurements. Front. Syst. Neurosci. 2012, 6, 69.
39. Hoekzema, E.; Carmona, S.; Ramos-Quiroga, J.A.; Richarte Fernandez, V.; Bosch, R.; Soliva, J.C.; Rovira, M.; Bulbena, A.; Tobeña, A.; Casas, M.; et al. An independent components and functional connectivity analysis of resting state fMRI data points to neural network dysregulation in adult ADHD. Hum. Brain Mapp. 2014, 35, 1261–1272.
40. Riaz, A.; Asad, M.; Alonso, E.; Slabaugh, G. Fusion of fMRI and non-imaging data for ADHD classification. Comput. Med. Imaging Graph. 2018, 65, 115–128.
41. Rubia, K.; Criaud, M.; Wulff, M.; Alegria, A.; Brinson, H.; Barker, G.; Stahl, D.; Giampietro, V. Functional connectivity changes associated with fMRI neurofeedback of right inferior frontal cortex in adolescents with ADHD. NeuroImage 2019, 188, 43–58.
42. Zhang, T.; Li, C.; Li, P.; Peng, Y.; Kang, X.; Jiang, C.; Li, F.; Zhu, X.; Yao, D.; Biswal, B.; et al. Separated Channel Attention Convolutional Neural Network (SC-CNN-Attention) to Identify ADHD in Multi-Site Rs-fMRI Dataset. Entropy 2020, 22, 893.
43. Chang, C.W.; Ho, C.C.; Chen, J.H. ADHD classification by a texture analysis of anatomical brain MRI data. Front. Syst. Neurosci. 2012, 6, 66.
44. Peng, X.; Lin, P.; Zhang, T.; Wang, J. Extreme learning machine-based classification of ADHD using brain structural MRI data. PLoS ONE 2013, 8, e79476.
45. Fischl, B. FreeSurfer. NeuroImage 2012, 62, 774–781.
46. Lim, L.; Marquand, A.; Cubillo, A.A.; Smith, A.B.; Chantiluke, K.; Simmons, A.; Mehta, M.; Rubia, K. Disorder-specific predictive classification of adolescents with attention deficit hyperactivity disorder (ADHD) relative to autism using structural magnetic resonance imaging. PLoS ONE 2013, 8, e63660.
47. Qureshi, M.N.I.; Oh, J.; Min, B.; Jo, H.J.; Lee, B. Multi-modal, multi-measure, and multi-class discrimination of ADHD with hierarchical feature extraction and extreme learning machine using structural and functional brain MRI. Front. Hum. Neurosci. 2017, 11, 157.
48. Sen, B.; Borle, N.C.; Greiner, R.; Brown, M.R. A general prediction model for the detection of ADHD and Autism using structural and functional MRI. PLoS ONE 2018, 13, e0194856.
49. Jiang, W.; Duan, K.; Rootes-Murdy, K.; Hoekstra, P.J.; Hartman, C.A.; Oosterlaan, J.; Heslenfeld, D.; Franke, B.; Buitelaar, J.; Arias-Vasquez, A.; et al. Structural brain alterations and their association with cognitive function and symptoms in Attention-deficit/Hyperactivity Disorder families. NeuroImage Clin. 2020, 27, 102273.

50. Sato, J.R.; Hoexter, M.Q.; Castellanos, X.F.; Rohde, L.A. Abnormal brain connectivity patterns in adults with ADHD: A coherence study. PLoS ONE 2012, 7, e45671.
51. Choi, J.; Jeong, B.; Lee, S.W.; Go, H.J. Aberrant development of functional connectivity among resting state-related functional networks in medication-naive ADHD children. PLoS ONE 2013, 8, e83516.
52. McLeod, K.R.; Langevin, L.M.; Goodyear, B.G.; Dewey, D. Functional connectivity of neural motor networks is disrupted in children with developmental coordination disorder and attention-deficit/hyperactivity disorder. NeuroImage Clin. 2014, 4, 566–575.
53. 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. 2015, 45, 2668–2679.
54. Mowinckel, A.M.; Alnæs, D.; Pedersen, M.L.; Ziegler, S.; Fredriksen, M.; Kaufmann, T.; Sonuga-Barke, E.; Endestad, T.; Westlye, L.T.; Biele, G. Increased default-mode variability is related to reduced task-performance and is evident in adults with ADHD. NeuroImage Clin. 2017, 16, 369–382.
55. Damiani, S.; Tarchi, L.; Scalabrini, A.; Marini, S.; Provenzani, U.; Rocchetti, M.; Oliva, F.; Politi, P. Beneath the surface: Hyper-connectivity between caudate and salience regions in ADHD fMRI at rest. Eur. Child Adolesc. Psychiatry 2020, 4, 619–631.
56. Guo, X.; Yao, D.; Cao, Q.; Liu, L.; Zhao, Q.; Li, H.; Huang, F.; Wang, Y.; Qian, Q.; Wang, Y.; et al. Shared and distinct resting functional connectivity in children and adults with attention-deficit/hyperactivity disorder. Transl. Psychiatry 2020, 10, 65.
57. Shao, L.; You, Y.; Du, H.; Fu, D. Classification of ADHD with fMRI data and multi-objective optimization. Comput. Methods Prog. Biomed. 2020, 196, 105676.
58. Chen, Y.; Tang, Y.; Wang, C.; Liu, X.; Zhao, L.; Wang, Z. ADHD classification by dual subspace learning using resting-state functional connectivity. Artif. Intell. Med. 2020, 103, 101786.
59. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. Nature 2015, 521, 436–444.
60. Gheisari, M.; Najafabadi, H.E.; Alzubi, J.A.; Gao, J.; Wang, G.; Abbasi, A.A.; Castiglione, A. OBPP: An ontology-based framework for privacy-preserving in IoT-based smart city. Future Gener. Comput. Syst. 2021, 123, 1–13.
61. Gao, J.; Wang, H.; Shen, H. Machine learning based workload prediction in cloud computing. In Proceedings of the 2020 29th International Conference on Computer Communications and Networks (ICCCN), Honolulu, HI, USA, 3–6 August 2020; pp. 1–9.
62. Gao, J.; Wang, H.; Shen, H. Smartly handling renewable energy instability in supporting a cloud datacenter. In Proceedings of the 2020 IEEE International Parallel and Distributed Processing

Symposium (IPDPS), New Orleans, LA, USA, 18–22 May 2020; pp. 769–778.

63. Gao, J.; Wang, H.; Shen, H. Task failure prediction in cloud data centers using deep learning. IEEE Trans. Serv. Comput. 2020.
64. Shen, D.; Wu, G.; Suk, H.I. Deep learning in medical image analysis. Annu. Rev. Biomed. Eng. 2017, 19, 221–248.
65. Litjens, G.; Kooi, T.; Bejnordi, B.E.; Setio, A.A.A.; Ciompi, F.; Ghafoorian, M.; Van Der Laak, J.A.; Van Ginneken, B.; Sánchez, C.I. A survey on deep learning in medical image analysis. Med. Image Anal. 2017, 42, 60–88.
66. Esteva, A.; Robicquet, A.; Ramsundar, B.; Kuleshov, V.; DePristo, M.; Chou, K.; Cui, C.; Corrado, G.; Thrun, S.; Dean, J. A guide to deep learning in healthcare. Nat. Med. 2019, 25, 24–29.
67. Mao, Z.; Su, Y.; Xu, G.; Wang, X.; Huang, Y.; Yue, W.; Sun, L.; Xiong, N. Spatio-temporal deep learning method for ADHD fMRI classification. Inf. Sci. 2019, 499, 1–11.
68. Riaz, A.; Asad, M.; Alonso, E.; Slabaugh, G. DeepFMRI: End-to-end deep learning for functional connectivity and classification of ADHD using fMRI. J. Neurosci. Methods 2020, 335, 108506.
69. Liu, S.; Zhao, L.; Wang, X.; Xin, Q.; Zhao, J.; Guttery, D.S.; Zhang, Y.D. Deep Spatio-Temporal Representation and Ensemble Classification for Attention deficit/Hyperactivity disorder. IEEE Trans. Neural Syst. Rehabil. Eng. 2020, 29, 1–10.