

References

1. Saleh A, Sukaik R, Abu-Naser SS. Brain Tumor Classification Using Deep Learning. In: 2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech); 2020. p. 131–136.
2. Qureshi SA, Hussain L, Ibrar U, Alabdulkreem E, Nour MK, Alqahtani MS, et al. Radiogenomic classification for MGMT promoter methylation status using multi-omics fused feature space for least invasive diagnosis through mpMRI scans. *Scientific reports*. 2023; 13(1):3291. <https://doi.org/10.1038/s41598-023-30309-4> PMID: 36841898
3. Hu Z, Wang J, Zhang C, Luo Z, Luo X, Xiao L, et al. Uncertainty Modeling for Multicenter Autism Spectrum Disorder Classification Using Takagi–Sugeno–Kang Fuzzy Systems. *IEEE Transactions on Cognitive and Developmental Systems*. 2022; 14(2):730–739. <https://doi.org/10.1109/TCDS.2021.3073368>
4. Chola Raja K, Kannimuthu S. Deep learning-based feature selection and prediction system for autism spectrum disorder using a hybrid meta-heuristics approach. *Journal of Intelligent & Fuzzy Systems*. 2023; p. 797–807. <https://doi.org/10.3233/JIFS-223694>
5. Niu M, Tao J, Liu B, Huang J, Lian Z. Multimodal spatiotemporal representation for automatic depression level detection. *IEEE transactions on affective computing*. 2020;.
6. Maqsood S, Damasėvičius R, Maskeliūnas R. Multi-modal brain tumor detection using deep neural network and multiclass SVM. *Medicina*. 2022; 58(8):1090. <https://doi.org/10.3390/medicina58081090> PMID: 36013557
7. Grampurohit S, Shalavadi V, Dhotargavi VR, Kudari M, Jolad S. Brain tumor detection using deep learning models. In: 2020 IEEE India Council International Subsections Conference (INDISCON). IEEE; 2020. p. 129–134.
8. Li Z, et al. Vision transformer-based weakly supervised histopathological image analysis of primary brain tumors. *iScience* 26, 1, 105872 (2023). <https://doi.org/10.1016/j.isci.2022.105872> PMID:

36647383

9. Qureshi SA, Raza SEA, Hussain L, Malibari AA, Nour MK, Rehman Au, et al. Intelligent ultra-light deep

learning model for multi-class brain tumor detection. *Applied Sciences*. 2022; 12(8):3715. [https://doi.](https://doi.org/10.3390/app12083715)

[org/10.3390/app12083715](https://doi.org/10.3390/app12083715)

10. Elshoky BRG, Younis EM, Ali AA, Ibrahim OAS. Comparing automated and non-automated machine

learning for autism spectrum disorders classification using facial images. *ETRI Journal*. 2022; 44(4):613–623. <https://doi.org/10.4218/etrij.2021-0097>

11. Rajagopalan SS. Computational behaviour modelling for autism diagnosis. In: *Proceedings of the 15th*

ACM on International conference on multimodal interaction; 2013. p. 361–364.

12. Wei Q, Cao H, Shi Y, Xu X, Li T. Machine learning based on eye-tracking data to identify Autism Spectrum Disorder: A systematic review and meta-analysis. *Journal of Biomedical Informatics*. 2022; p.

104254. PMID: 36509416

13. Mier W, Mier D. Advantages in functional imaging of the brain. *Frontiers in Human Neuroscience*. 2015;

9. <https://doi.org/10.3389/fnhum.2015.00249> PMID: 26042013

14. Daliri mr, Behroozi M. Advantages and Disadvantages of Resting State Functional Connectivity Magnetic Resonance Imaging for Clinical Applications. *OMICS Journal of Radiology*. 2014; 3. [https://doi.](https://doi.org/10.4172/2167-7964.1000e123)

[org/10.4172/2167-7964.1000e123](https://doi.org/10.4172/2167-7964.1000e123)

15. Jiang X, Yan J, Zhao Y, Jiang M, Chen Y, Zhou J, et al. Characterizing functional brain networks via

spatio-temporal attention 4D convolutional neural networks (STA-4DCNNs). *Neural Networks*. 2023;

158:99–110. <https://doi.org/10.1016/j.neunet.2022.11.004> PMID: 36446159

16. Hutchison RM, Womelsdorf T, Allen EA, Bandettini PA, Calhoun VD, Corbetta M, et al. Dynamic functional connectivity: promise, issues, and interpretations. *Neuroimage*. 2013; 80:360–378. [https://doi.](https://doi.org/10.1016/j.neuroimage.2013.05.079)

[org/10.1016/j.neuroimage.2013.05.079](https://doi.org/10.1016/j.neuroimage.2013.05.079) PMID: 23707587

17. Menon SS, Krishnamurthy K. A comparison of static and dynamic functional connectivities for identifying subjects and biological sex using intrinsic individual brain connectivity. *Scientific reports*. 2019; 9

(1):5729. <https://doi.org/10.1038/s41598-019-42090-4> PMID: 30952913

18. Patil AU, Ghate S, Madathil D, Tzeng OJ, Huang HW, Huang CM. Static and dynamic functional connectivity supports the configuration of brain networks associated with creative cognition. *Scientific*

reports. 2021; 11(1):165. <https://doi.org/10.1038/s41598-020-80293-2> PMID: 33420212

19. Volkmar FR. *Encyclopedia of autism spectrum disorders*. Springer; 2021.

20. Lyall K, Rando J, Toroni B, Ezech T, Constantino JN, Croen LA, et al. Examining shortened versions of

the Social Responsiveness Scale for use in autism spectrum disorder prediction and as a quantitative trait measure: Results from a validation study of 3–5 year old children. *JCPP advances*. 2022; 2(4):

e12106. <https://doi.org/10.1002/jcv2.12106> PMID: 36741204

21. Borges L, Otoni F, Lima THd, Schelini PW. Social Responsibility Scale (SRS-2): Validity Evidence

Based on Internal Structure. *Psicologia: Teoria e Pesquisa*. 2023; 39:11.

22. Kovacs Balint Z, Raper J, Michopoulos V, Howell LH, Gunter C, Bachevalier J, et al. Validation of the

Social Responsiveness Scale (SRS) to screen for atypical social behaviors in juvenile macaques.

PLOS ONE. 2021; 16(5):1–19. <https://doi.org/10.1371/journal.pone.0235946> PMID: 34014933

23. Eslami T, Almuqhim F, Raiker JS, Saeed F. Machine learning methods for diagnosing autism spectrum

disorder and attention-deficit/hyperactivity disorder using functional and structural MRI: A survey. *Frontiers in neuroinformatics*. 2021; p. 62. <https://doi.org/10.3389/fninf.2020.575999> PMID: 33551784

24. Bahathiq RA, Banjar H, Bamaga AK, Jarraya SK. Machine learning for autism spectrum disorder diagnosis using structural magnetic resonance imaging: Promising but challenging. *Frontiers in Neuroinformatics*. 2022; 16:949926. <https://doi.org/10.3389/fninf.2022.949926> PMID: 36246393

25. MartinD23. Pixabay Creatures <https://pixabay.com/illustrations/clipboard-checklist-business-list2537569/>. Content License: <https://pixabay.com/service/terms/>

26. toubibe. Pixabay Creatures <https://pixabay.com/illustrations/mri-magnetic-resonance-roentgen782457/>. Content License: <https://pixabay.com/service/terms/>
27. Rudin C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature machine intelligence*. 2019;1(5):206–215
28. Alves CL, Toutain TGdO, de Carvalho Aguiar P, Pineda AM, Roster K, Thielemann C, et al. Diagnosis of autism spectrum disorder based on functional brain networks and machine learning. *Scientific Reports*. 2023;13(1):8072
29. Mash, L. E., Linke, A. C., Olson, L. A., Fishman, I., Liu, T. T., and Müller, R.- A. (2019). Transient states of network connectivity are atypical in autism: a dynamic functional connectivity study. *Hum. Brain Mapp*. 40, 2377–2389. doi: 10.1002/hbm.24529
30. Albert R, Barabási AL. Statistical mechanics of complex networks. *Reviews of modern physics*. 2002;74(1):47.
31. Freeman LC. A set of measures of centrality based on betweenness. *Sociometry*. 1977; p. 35–41
32. Freeman LC. Centrality in social networks conceptual clarification. *Social networks*. 1978;1(3):215–239.
33. Albert R, Jeong H, Barabási AL. Diameter of the world-wide web. *nature*. 1999;401(6749):130–131.
34. Newman ME. The structure and function of complex networks. *SIAM review*. 2003;45(2):167–256/ Newman ME. Assortative mixing in networks. *Physical review letters*. 2002;89(20):208701
35. Kleinberg JM. Hubs, authorities, and communities. *ACM computing surveys (CSUR)*. 1999;31(4es):5–es
36. Hage P, Harary F. Eccentricity and centrality in networks. *Social networks*. 1995;17(1):57–63
37. Bonacich P. Power and centrality: A family of measures. *American journal of sociology*. 1987;92(5):1170–1182
38. Eppstein D, Paterson MS, Yao FF. On nearest-neighbor graphs. *Discrete & Computational Geometry*. 1997;17(3):263–282
39. Doyle J, Graver J. Mean distance in a graph. *Discrete Mathematics*. 1977;17(2):147–154
40. Dehmer M, Mowshowitz A. A history of graph entropy measures. *Information Sciences*. 2011;181(1):57–78

41. Watts DJ, Strogatz SH. Collective dynamics of ‘small-world’ networks. *Nature*. 1998;393(6684):440–442/ Newman ME, Watts DJ, Strogatz SH. Random graph models of social networks. *Proceedings of the National Academy of Sciences*. 2002;99(suppl 1):2566–2572
42. Snijders TA. The degree variance: an index of graph heterogeneity. *Social networks*. 1981;3(3):163–174.
43. Seidman SB. Network structure and minimum degree. *Social networks*. 1983;5(3):269–287
44. Newman M. *Networks: an introduction*. Oxford university press; 2010.
45. Anderson BS, Butts C, Carley K. The interaction of size and density with graph-level indices. *Social networks*. 1999;21(3):239–267.
46. Latora V, Marchiori M. Economic small-world behavior in weighted networks. *The European Physical Journal B-Condensed Matter and Complex Systems*. 2003;32(2):249–263