



20. BÖLÜM

DİKKAT EKSİKLİĞİ HİPERAKTİVİTE BOZUKLUĞU VE YAPAY ZEKA

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GİRİŞ

Dikkat eksikliği hiperaktivite bozukluğu (DEHB), çocukluk çağının en sık rastlanılan ruhsal bozukluklarından birisidir. Dikkat dağınıklığı, aşırı aktivite veya zayıf öz-denetim (self-control) başlıca semptomlarıdır (1). Amerikan Psikiyatri Birliği (APA), DEHB'yi dikkat eksikliğinin ön planda olduğu tip, hiperaktivite-impulsivitenin ön planda olduğu tip ve kombine tip olmak üzere üç alt gruba ayırmıştır (2). DEHB'nin etiyopatogenezi heterojen olup, genetik, çevresel ve nöronal etkenler rol oynamaktadır.

APA'nın DSM el kitabında DEHB ile ilgili teşhisin duyarlılığı %70-%90 arasındadır. Klinik uygulamadaki teşhisler klinisyenin gözlemlerine ve semptom anketlerine dayanmaktadır. DEHB'yi sınıflandırmak ve teşhis etmek için daha nicel ve objektif analizlerin geliştirilmesi, nörobilim araştırmalarının önemli bir hedefidir. Bu amaçla farklı verilerden faydalanılarak makine öğrenmesi tabanlı, yapay zekaya dayanan yöntemler geliştirilmektedir.

Kitabımızın bu bölümünde DEHB ve Yapay Zeka ile ilgili genel bilgilerin ardından, DEHB'nin sınıflandırılması ve teşhisinde Yapay Zeka'nın rolünü araştıran çalışmalara yer verilmiştir.

DEHB TANIMI

Dikkat Eksikliği Hiperaktivite Bozukluğu (DEHB), çocukluk çağında başlayan, kişinin yaşına ve gelişim düzeyine uygun olmayan dikkatsizlik, hiperak-

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Yapay Zeka yaklaşımlarıyla DEHB teşhisini araştıran diğer çalışmalara örnek olarak; DEHB hastalarının madde bağımlılığına yakalanma olasılığının kestirimi konusunda çalışılarak, yinelemeli bir derin öğrenme sinir ağı türü olan uzun-kısa süreli bellek (LSTM) kullanılmış ve beyin kaudat nükleus adı verilen kısmının MR görüntülerinin bölütlenmesi temeline dayanan bir method ile analiz edilmiştir (62, 63); kişilerin davranışlarının renk ve derinlik bilgisi içeren görselleri kullanılarak DEHB'nin teşhisi konulmaya çalışılmıştır (64); DEHB-200 veri seti kullanılarak, öznelik seçme algoritmaları ile uygun öznelikler belirlenmiş ve daha sonra Destek Vektör Makinaları ile sınıflandırma yapılmıştır (65); DEHB'nin Obstrüktif uyku apnesinden ayırt edilmesine yönelik farklı makine öğrenme algoritmalarından faydalanılmıştır (66). Ortaya konan makine öğrenmesi tabanlı tüm bu yöntemlerde %70-%90 aralığında başarımlar elde edilmiştir.

SONUÇ

Yapay Zeka yöntemleriyle DEHB teşhisinin konulması daha objektif, daha kısa zaman diliminde gerçekleşmekte ve daha az yorucu olmaktadır. Bu yaklaşımlar yalnızca zamandan, insan gücünden ve diğer kaynaklardan tasarruf sağlamakla kalmayıp, aynı zamanda olası insan önyargısını da önlemektedir. Bu konuda daha fazla çalışmaların yapılmasına ihtiyaç vardır.

KAYNAKLAR

1. Kooij SJ, Bejerot S, Blackwell A, Caci H, Casas-Brugué M, Carpentier PJ, et al. European consensus statement on diagnosis and treatment of adult ADHD: The European Network Adult ADHD. *BMC psychiatry*. 2010;10(1):1-24.
2. APA A. Diagnostic and Statistical Manual of Mental Disorders, 4th edn, text revision (DSM-IV-TR). Washington DC: APA. 2000.
3. Pliszka S. AACAP Work Group on Quality Issues Practice parameter for the assessment and treatment of children and adolescents with attention-deficit/hyperactivity disorder. *J Am Acad Child Adolesc Psychiatry*. 2007;46(7):894-921.
4. Polanczyk G, De Lima MS, Horta BL, Biederman J, Rohde LA. The worldwide prevalence of ADHD: a systematic review and metaregression analysis. *American journal of psychiatry*. 2007;164(6):942-8.
5. Willcutt EG. The prevalence of DSM-IV attention-deficit/hyperactivity disorder: a meta-analytic review. *Neurotherapeutics*. 2012;9(3):490-9.
6. Polanczyk G, Jensen P. Epidemiologic considerations in attention deficit hyperactivity disorder: a review and update. *Child and adolescent psychiatric clinics of North America*. 2008;17(2):245-60.
7. Akutagava-Martins GC, Salatino-Oliveira A, Kieling CC, Rohde LA, Hutz MH. Genetics of attention-deficit/hyperactivity disorder: current findings and future directions. *Expert review of neurotherapeutics*. 2013;13(4):435-45.
8. Biederman J, Faraone S, Milberger S, Guite J, Mick E, Chen L, et al. A prospective 4-year follow-up study of attention-deficit hyperactivity and related disorders. *Archives of general psychiatry*. 1996;53(5):437-46.

9. Ingram S, Hechtman L, Morgenstern G. Outcome issues in ADHD: Adolescent and adult long-term outcome. *Mental retardation and developmental disabilities research reviews*. 1999;5(3):243-50.
10. Weiss G, Hechtman L, Milroy T, Perlman T. Psychiatric status of hyperactives as adults: a controlled prospective 15-year follow-up of 63 hyperactive children. *Journal of the American Academy of Child Psychiatry*. 1985;24(2):211-20.
11. Weis M WG. Attention deficit hiperactivity disorder. . In: Lewis M, ed *Child and Adolescent Psychiatry: A comprehensive Textbook* 3rd ed Philadelphia: Lippincott Williams and Wilkins;. 2002:p. 645-70.
12. Homer C, Baltz R, Hickson G, Miles P, Newman T, Shook J, et al. Clinical practice guideline: diagnosis and evaluation of the child with attention-deficit/hyperactivity disorder. *Pediatrics*. 2000;105(5):1158-70.
13. Improvement SoA-DHDCoQ. Clinical practice guideline: treatment of the school-aged child with attention-deficit/hyperactivity disorder. *Pediatrics*. 2001;108(4):1033-44.
14. Pang Z, Yuan H, Zhang Y-T, Packirisamy M. Guest Editorial Health Engineering Driven by the Industry 4.0 for Aging Society. *IEEE Journal of Biomedical and Health Informatics*. 2018;22(6):1709-10.
15. Choi K-S, Lee CS, Louderback ER. Historical Evolutions of Cybercrime: From Computer Crime to Cybercrime. *The Palgrave Handbook of International Cybercrime and Cyberdeviance*. 2020:27-43.
16. Simon HA. Artificial intelligence: where has it been, and where is it going? *IEEE Transactions on Knowledge and Data Engineering*. 1991;3(2):128-36.
17. McCarthy J. *Artificial intelligence, logic and formalizing common sense*. Philosophical logic and artificial intelligence: Springer; 1989. p. 161-90.
18. TURING IBA. Computing machinery and intelligence-AM Turing. *Mind*. 1950;59(236):433.
19. Jiang F, Jiang Y, Zhi H, Dong Y, Li H, Ma S, et al. Artificial intelligence in healthcare: past, present and future. *Stroke and vascular neurology*. 2017;2(4):230-43.
20. Hengstler M, Enkel E, Duelli S. Applied artificial intelligence and trust—The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*. 2016;105:105-20.
21. Beam AL, Kohane IS. Translating artificial intelligence into clinical care. *Jama*. 2016;316(22):2368-9.
22. Miotto R, Wang F, Wang S, Jiang X, Dudley JT. Deep learning for healthcare: review, opportunities and challenges. *Briefings in bioinformatics*. 2018;19(6):1236-46.
23. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nature medicine*. 2019;25(1):44-56.
24. Reddy S, Fox J, Purohit MP. Artificial intelligence-enabled healthcare delivery. *Journal of the Royal Society of Medicine*. 2019;112(1):22-8.
25. Holch J, Ricard I, Stintzing S, von Weikersthal LF, Decker T, Kiani A, et al. Relevance of baseline carcinoembryonic antigen for first-line treatment against metastatic colorectal cancer with FOLFIRI plus cetuximab or bevacizumab (FIRE-3 trial). *European Journal of Cancer*. 2019;106:115-25.
26. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJ. Artificial intelligence in radiology. *Nature Reviews Cancer*. 2018;18(8):500-10.
27. Sengupta PP, Adjeroh DA. Will artificial intelligence replace the human echocardiographer? Clinical considerations. *Am Heart Assoc*; 2018.
28. Vidal-Alaball J, Fibla DR, Zapata MA, Marin-Gomez FX, Fernandez OS. Artificial intelligence for the detection of diabetic retinopathy in primary care: protocol for algorithm development. *JMIR research protocols*. 2019;8(2):e12539.
29. Topol E. *Deep medicine: how artificial intelligence can make healthcare human again*: Hachette UK; 2019.

30. Wang Y, Kung L, Byrd TA. Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change*. 2018;126:3-13.
31. Miller DD, Brown EW. Artificial intelligence in medical practice: the question to the answer? *The American journal of medicine*. 2018;131(2):129-33.
32. Gabbard GO, Crisp-Han H. The early career psychiatrist and the psychotherapeutic identity. *Academic Psychiatry*. 2017;41(1):30-4.
33. Janssen RJ, Mourão-Miranda J, Schnack HG. Making individual prognoses in psychiatry using neuroimaging and machine learning. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*. 2018;3(9):798-808.
34. Luxton DD. Artificial intelligence in psychological practice: Current and future applications and implications. *Professional Psychology: Research and Practice*. 2014;45(5):332.
35. Vincent P, Larochelle H, Lajoie I, Bengio Y, Manzagol P-A, Bottou L. Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. *Journal of machine learning research*. 2010;11(12).
36. Shatte AB, Hutchinson DM, Teague SJ. Machine learning in mental health: a scoping review of methods and applications. *Psychological medicine*. 2019;49(9):1426-48.
37. Iniesta R, Stahl D, McGuffin P. Machine learning, statistical learning and the future of biological research in psychiatry. *Psychological medicine*. 2016;46(12):2455-65.
38. Bzdok D, Meyer-Lindenberg A. Machine learning for precision psychiatry: opportunities and challenges. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*. 2018;3(3):223-30.
39. Jeste DV, Glorioso D, Lee EE, Daly R, Graham S, Liu J, et al. Study of independent living residents of a continuing care senior housing community: sociodemographic and clinical associations of cognitive, physical, and mental health. *The American Journal of Geriatric Psychiatry*. 2019;27(9):895-907.
40. WANG L, WANG L. Disease Prediction by Machine Learning Over Big Data From Healthcare Communities.
41. Karthik L, Kumar G, Keswani T, Bhattacharyya A, Chandar SS, Rao KB. Protease inhibitors from marine actinobacteria as a potential source for antimalarial compound. *PloS one*. 2014;9(3):e90972.
42. Srividya M, Mohanavalli S, Bhalaji N. Behavioral modeling for mental health using machine learning algorithms. *Journal of medical systems*. 2018;42(5):88.
43. Wiens J, Shenoy ES. Machine learning for healthcare: on the verge of a major shift in healthcare epidemiology. *Clinical Infectious Diseases*. 2018;66(1):149-53.
44. Bzdok D, Krzywinski M, Altman N. Machine learning: supervised methods. *Nature Publishing Group*; 2018.
45. Miotto R, Li L, Kidd BA, Dudley JT. Deep patient: an unsupervised representation to predict the future of patients from the electronic health records. *Scientific reports*. 2016;6(1):1-10.
46. Collaboration SI. *Machine Learning and Health Care Disparities in Dermatology*. 2018.
47. Fabris F, De Magalhães JP, Freitas AA. A review of supervised machine learning applied to ageing research. *Biogerontology*. 2017;18(2):171-88.
48. Graham S, Depp C, Lee EE, Nebeker C, Tu X, Kim H-C, et al. Artificial intelligence for mental health and mental illnesses: an overview. *Current psychiatry reports*. 2019;21(11):116.
49. Dy JG, Brodley CE. Feature selection for unsupervised learning. *Journal of machine learning research*. 2004;5(Aug):845-89.
50. Shickel B, Tighe PJ, Bihorac A, Rashidi P. Deep EHR: a survey of recent advances in deep learning techniques for electronic health record (EHR) analysis. *IEEE journal of biomedical and health informatics*. 2017;22(5):1589-604.
51. Hirschberg J, Manning CD. Advances in natural language processing. *Science*. 2015;349(6245):261-6.

52. Calvo RA, Milne DN, Hussain MS, Christensen H. Natural language processing in mental health applications using non-clinical texts. *Natural Language Engineering*. 2017;23(5):649-85.
53. Demner-Fushman D, Chapman WW, McDonald CJ. What can natural language processing do for clinical decision support? *Journal of biomedical informatics*. 2009;42(5):760-72.
54. Cambria E, White B. Jumping NLP curves: A review of natural language processing research. *IEEE Computational intelligence magazine*. 2014;9(2):48-57.
55. Öztoprak H, Toycan M, Alp YK, Arıkan O, Doğutepe E, Karakaş S. Makina temelli öğrenim sistemi: DEHB olan ve olmayan katılımcıların sınıflandırılması. 2017.
56. Mueller A, Candrian G, Kropotov JD, Ponomarev VA, Baschera G-M, editors. Classification of ADHD patients on the basis of independent ERP components using a machine learning system. *Nonlinear biomedical physics*; 2010: Springer.
57. Tenev A, Markovska-Simoska S, Kocarev L, Pop-Jordanov J, Müller A, Candrian G. Machine learning approach for classification of ADHD adults. *International Journal of Psychophysiology*. 2014;93(1):162-6.
58. Anuradha J, Ramachandran V, Arulalan K, Tripathy B, editors. Diagnosis of ADHD using SVM algorithm. *Proceedings of the Third Annual ACM Bangalore Conference*; 2010.
59. Kim J-W, Sharma V, Ryan ND. Predicting Methylphenidate Response in ADHD Using Machine Learning Approaches. *International Journal of Neuropsychopharmacology*. 2015;18(11).
60. ÇİÇEK G, ÖZMEN A, AKAN A. Derin Öğrenmeyi Kullanarak Veri Artırımının DEHB Tanı Modeline Etkisi The Effect of Data Augmentation on ADHD Diagnostic Model using Deep Learning.
61. Vahid A, Bluschke A, Roessner V, Stober S, Beste C. Deep learning based on event-related EEG differentiates children with ADHD from healthy controls. *Journal of clinical medicine*. 2019;8(7):1055.
62. Fouladvand S, Hankosky ER, Henderson DW, Bush H, Chen J, Dwoskin LP, et al., editors. Predicting Substance Use Disorder in ADHD Patients using Long-Short Term Memory Model. 2018 IEEE International Conference on Healthcare Informatics Workshop (ICHI-W); 2018: IEEE.
63. Igual L, Soliva JC, Hernández-Vela A, Escalera S, Vilarroya O, Radeva P, editors. Supervised brain segmentation and classification in diagnostic of attention-deficit/hyperactivity disorder. 2012 International Conference on High Performance Computing & Simulation (HPCS); 2012: IEEE.
64. Jaiswal S, Valstar MF, Gillott A, Daley D, editors. Automatic detection of ADHD and ASD from expressive behaviour in RGBD data. 2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017); 2017: IEEE.
65. Çiçek G, Özmen A, Akan A, editors. The Effect of Data Augmentation on ADHD Diagnostic Model using Deep Learning. 2019 Medical Technologies Congress (TIPTEKNO); 2019: IEEE.
66. Chu K-C, Huang H-J, Huang Y-S, editors. Machine learning approach for distinction of ADHD and OSA. 2016 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM); 2016: IEEE.