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A Brief Review of Artificial Intelligence Applications and Algorithms for Psychiatric Disorders

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ABSTRACT

A number of brain research projects have recently been carried out to study the etiology and mechanisms of psychiatric disorders. Although psychiatric disorders are part of the brain sciences, psychiatrists still diagnose them based on subjective experience rather than by gaining insights into the pathophysiology of the diseases. Therefore, it is urgent to have a clear understanding of the etiology and pathogenesis of major psychiatric diseases, which can help in the development of effective treatments and interventions. Artificial intelligence (AI)-based applications are being quickly developed for psychiatric research and diagnosis, but there is no systematic review that summarizes their applications. For this reason, this study briefly reviews three main brain observation techniques used to study psychiatric disorders—namely, magnetic resonance imaging (MRI), electroencephalography (EEG), and kinesics-based diagnoses—along with related AI applications and algorithms. Finally, we discuss the challenges, opportunities, and future study directions of AI-based applications.

1. Introduction

According to the Global Burden of Disease Study in 1990 and 2010 [1], the main causes of the fourth largest disease burden measured in disability-adjusted life years (DALYs) are mental and substance-use disorders [2,3], which are jointly considered to be the leading cause of lived-with disability worldwide.

A number of brain research projects have recently been carried out to study the etiology and mechanisms of psychiatric disorders [4], which could help improve brain interventional and clinical treatment capabilities [5]. For example, the United States proposed the Brain Research through Advancing Innovative Neuroethology initiative [4] in 2013, the European Union initiated the Human Brain Project (HBP) [4] in 2013, and Japan started the Japan Brain Bank Network project in 2014 [5]. China launched the Chinese Brain Project in 2016, which covers both basic research for the neural mechanisms of brain disease and clinical research on brain disease [6].

Although psychiatric disorders are a research area in brain science, most psychiatrists still diagnose them based on subjective experience rather than by gaining insights into the pathophysiology of the diseases [7,8]. As a result, psychiatrists may misdiagnose diseases and incorrectly delineate distinct paths of treatment. Therefore, it is urgent to develop a clear understanding of the etiology and pathogenesis of major psychiatric diseases in order to develop effective treatments and interventions for major brain diseases.

In recent years, artificial intelligence (AI)-based applications have rapidly been developed for psychiatric research and diagnosis [9–15]. For example, Jan et al. [16] proposed an AI system to monitor depression that can predict Beck Depression Inventory II (BDI-II) scores from vocal and visual expressions. In addition, Wen et al. [17] extracted multi-type gray–white matter features based on multimodal neuroimaging and used a multicore learning classifier to assign weights to the kernel functions of each feature.

However, to the best of our knowledge, there is no systematic review that illustrates the use of these AI-based applications for

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psychiatric research and diagnosis. Thus, we will briefly review commonly used AI-based applications for psychiatric disorders and illustrate how to apply AI technology to explore biomarkers for psychiatric disorders.

2. Major AI-related techniques for psychiatric disorder diagnosis

AI techniques [18,19] are being progressively introduced for psychiatric disorders. Brain structure and function are the most important biological phenotypes and key diagnostic biomarkers for psychiatric disorders [20]. Therefore, AI-related techniques that can obtain detailed information to characterize different psychiatric disorders should be used for the diagnosis of these diseases [16].

Fig. 1 describes three major techniques for brain observation in the study of psychiatric disorders: magnetic resonance imaging (MRI), electroencephalography (EEG), and kinesics diagnosis [21]. We will subsequently discuss their related AI-based applications.

2.1. Magnetic resonance imaging

MRI is the predominant technique for behavioral and cognitive neuroscience since it can explore obvious psychiatric abnormalities that cannot be detected by computed tomography (CT) [22–25]. At present, commonly used AI technologies for brain imaging include multitask/multimodal learning, classification, kernel, and deep learning methods [26], which can help in effectively analyzing existing disease data for key biomarkers exploration and increasing the capacity for clinical brain disease treatment [24,25].

Although many AI-related applications have been developed to assist MRI [26–28], this section only focuses on convolutional neural networks (CNNs) [29] and deep neural networks (DNNs) [30–32], which are employed in neuroimaging studies to elucidate the neural correlates of psychiatric disorders [30,33–36]. For example, Hosseini-Asl et al. [37] proposed a new depth-supervised adaptive three-dimensional (3D) CNN that can automatically extract and recognize Alzheimer's disease features, capture changes caused by Alzheimer's disease, and use these networks to analyze and recognize MRI images. In addition, Koyamada et al. [38] built up a subject-transfer decoder using a DNN. It is trained by a functional MRI (fMRI) dataset in the Human Connectome Project (HCP), the decoder of which has been assessed as having higher decoding accuracy than other methods.

Although MRI is currently an important tool for diagnosis in general, it still has several major shortcomings. First, it requires extensive computer configurations. Second, big data is needed to optimize the key parameters of the model. Third, the imaging process takes a long time. Thus, the question of how to improve the current AI-based applications to solve these problems for MRI is an important future research direction.

2.2. Electroencephalography

Diagnosis and treatment of human brain and nervous system diseases can be performed by detecting and recording human EEG signals. EEG signals are critical for both understanding how the human brain processes information and diagnosing psychiatric disorders [39]. In comparison with CT and MRI, EEG has a higher temporal resolution [40]. Therefore, despite the limited spatial resolution of EEG, it is still a valuable tool for research and diagnostics, especially when specified studies require time resolution in the millisecond range, such as studies on anxiety, psychosis, and depression [41].

Here, we focus on describing the application of the classical machine learning algorithm for EEGs. Since EEG data is represented by a graph, it is always analyzed by AI-based models [42–45]. For example, Field and Diego [46] employed linear discriminant analysis to process EEG data and obtained 67% accuracy when classifying normal patients and patients with depression. In addition, Iosifescu et al. [47] employed a support vector machine (SVM) to process resting-state EEG data for 88 subjects at the midpoint of the eight-lead connection at the forehead and achieved a 70% classification accuracy. Moreover, Bisch et al. [48] used logistic regression (LR) to classify a nine-lead EEG for depression with an 83.3% classification accuracy.

Although EEGs can simplify the data acquisition process, they encounter information loss. More importantly, too many undetermined factors in EEG data result in a large amount of noise in the classification decision. Therefore, developing a machine learning model that is more suitable for EEG data is a future research direction.

2.3. Kinesics

Kinesics data (including behavioral [49], facial [50], and other data [48]) is becoming very important for the study of the pathogenesis, development transition, and diagnosis assistance of

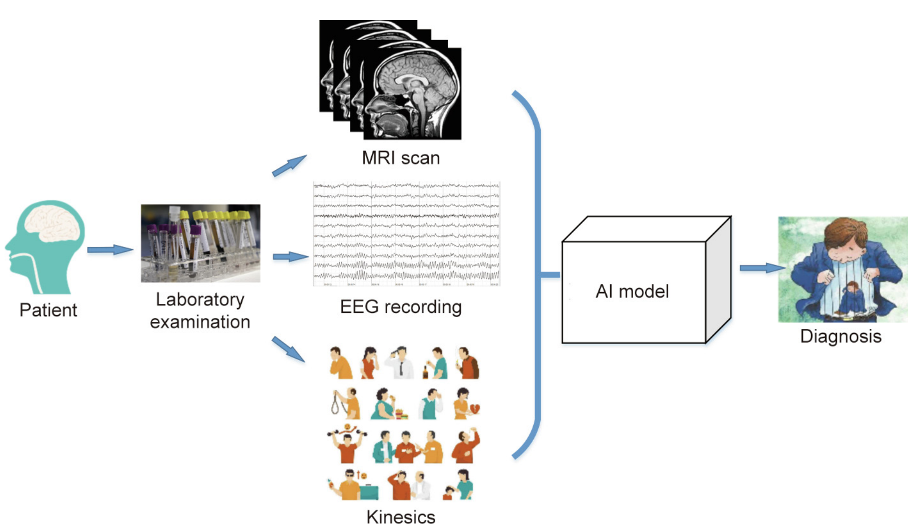

Fig. 1. Major observation techniques for psychiatric disorders.

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psychiatric disorders. AI-based technologies are widely employed to analyze such data to help diagnose and predict psychiatric disorders.

Many AI-related applications have recently been developed for kinesics-based diagnoses [50–52]. For example, Wang et al. [53] proposed a computational approach to develop probabilistic facial expression profiles for video data, which can automatically quantify the difference in emotional expression between patients with psychiatric disorders (e.g., schizophrenia) and healthy controls [16]. Zhu et al. [54] implemented automatic diagnosis of depression by means of a deep learning algorithm, which significantly improved the depression prediction performance by reducing the mean absolute error by 30.3%. In addition, Kaletsch et al. [55] examined differences in emotional expression by body movements between patients with major depressive disorder (MDD) and their healthy counterparts, and demonstrated that patients with MDD are more negative than their healthy counterparts.

In addition, Dhamecha et al. [56] proposed an algorithm to investigate human and machine performance for recognizing/verifying disguised faces [57]. The method can identify disguised face patches and account for this information to obtain improved matching accuracy by automatically localized feature descriptors. The experiments showed that the proposed algorithm can not only outperform popular commercial systems, but also evaluate the disguised face images when they are matched.

In general, with the development of AI and precision medicine, collecting and analyzing kinesics data will become easier, cheaper, and more convenient. Moreover, kinesics data could help to improve models' predictive accuracy, reduce the misdiagnosis rate, and assist psychiatrists in diagnosing and treating psychiatric disorders.

3. Artificial intelligence algorithms

3.1. Bayesian model

In AI, the naïve Bayes classifier [58–60] is a general term for a classification algorithm. The naïve Bayesian method is a classification method based on Bayes' theorem and characteristic condition-independent hypothesis.

Recent studies have often employed Bayesian models to diagnose psychiatric disorders. For example, the Strüngmann Forum on Computational Psychiatry [61–63] proposes using Bayesian inference to connect underlying causes (genetics and sociological phenomena [15,64]), latent hypothesized theoretical constructs, and symptoms [65]. Furthermore, Grove et al. [66] used a Bayesian model comparison approach to explore the relationship between visual integration and general cognition. The results showed that a Bayesian model can draw a comparison of the disease categorization systems and have common psychopathological information from diagnostic groups.

3.2. Logistic regression

In statistics, logistic models [67,68] (or logit models) are widely used statistical models, and LR is an important AI algorithm [68,69]. Recent studies often employ LR models to diagnose psychiatric disorders. For example, Hagen et al. [70] evaluated the associations between psychological distress and two cognitive screening tools by means of a LR method. The results demonstrated that performance-based assessment could reduce the impact of psychological distress on cognitive screening.

In addition, Barker et al. [71] employed models of multivariable LR to predict 30-day psychiatric readmission. Their findings are considered to be crucial predictors for psychiatric readmission, and have provided a better way of readmission prediction.

Shen et al. [72] generated a risk stratification model to obtain the odds ratio (OR) of psychiatric comorbidities by a classification and regression tree method. Using the LR method, the OR of psychiatric comorbidities was calculated between subjects with and without borderline personality disorder.

In general, the accuracy of LR models is so high that they are commonly applied in clinical practice.

3.3. Decision tree

A decision tree [73] is a flowchart-like diagram that shows the various outcomes from a series of decisions, including chance event outcomes and utility. Decision trees are one of the most widely and broadly used algorithms for supervised classification learning. In AI, a decision tree is a predictive model that represents a mapping between object properties and object values. Most modern decision tree learning algorithms adopt a purity-based heuristic [74]. Information gain, $\mathrm{gain}(D,X)$, is defined by Eq. (1) [75,76].

$$\mathrm{gain}(D,X)=\mathrm{info}(D)-\sum_{x}\frac{|D_x|}{|D|}\mathrm{info}(D_x) \tag{1}$$

where D is a set of training instances, X is an attribute, x is its value, D_x is a subset of D consisting of the instances with $X = x$, and $\mathrm{info}(D)$ is defined as shown in Eq. (2).

$$\mathrm{info}(D)=-\sum_{i=1}^{m}p_i\log_2(p_i) \tag{2}$$

where p_i is estimated by the percentage of instances and m is the number of classes.

Next, we detail two commonly used decision tree applications for psychiatric disorders.

Carpenter et al. [77] used the decision tree algorithm to test whether individual Preschool Age Psychiatric Assessment (PAPA) items can predict whether a child is likely to have generalized anxiety disorder (GAD) or separation anxiety disorder (SAD). They used a decision tree to identify children who were on the brink of experiencing anxiety disorder, and their results showed that the decision tree can achieve accurate prediction up to 96% for both GAD and SAD.

With a decision tree, Scattler et al. [78] analyzed data from the Spence Children's Anxiety Scale (SCAS) and SCAS-P obsessive–compulsive disorder subscales, and worked out two screening algorithms to diagnose obsessive–compulsive disorder from a combined clinical and community sample of children and families. The results showed that the algorithms that reduced the number of SCAS-P items needed to make a diagnosis of obsessive–compulsive disorder diagnoses up to 67%–83% without sacrificing the nature relative to the full subscales.

3.4. Support vector machines

The SVM is a current supervised learning method, the decision boundary of which is the maximum margin hyperplane for solving learning samples [79]. It can be described as follows: Start from a training dataset of n points of the form $(\vec{\boldsymbol{x}}_i, y_i), \ldots, (\vec{\boldsymbol{x}}_n, y_n)$, where $y_i \in \{-1, 1\}$ is used to denote the class labels. Each $\vec{\boldsymbol{x}}_i$ is a p-dimensional real vector. The goal is to find the maximum margin hyperplane that divides the group of points $\vec{\boldsymbol{x}}_i$ for which $y_i = 1$ from the group of points for which $y_i = -1$.

SVM models have been commonly used for diagnosing psychiatric disorders. For example, in order to describe users' situations, Peng et al. [80] employed a multi-kernel SVM-based model to locate potential users who might suffer from depression by

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extracting three social methods (user microblog text, user profile, and user behaviors). Based on a multiclass SVM, Al-Shargie et al. [81] put forward a discriminant analysis method. The results showed that the method could discriminate between different stress levels for EEG with a 94.79% average classification accuracy.

3.5. Deep learning

Classic machine learning methods, such as the Bayesian model and SVM, have been widely employed in psychiatry and neuroscience [64–66] studies for a long time. At present, deep learning [82–84], which is a hot machine learning research direction, outperforms the aforementioned AI models by a considerable margin [85–87].

Deep learning refers to a set of algorithms on a multi-layer neural network that uses various machine learning algorithms to solve various problems such as images and text. Combined with low-level features, deep learning can develop more abstract high-level attribute categories or features that can discover distributed feature representations of data. Weight updating can be solved by the stochastic gradient descent method using the following formula:

$$\Delta w(t+1) = \Delta w(t) + \eta \frac{\partial C}{\partial w} \tag{3}$$

where $\Delta w(t)$ is the weight of time t, η is the learning rate, and C is the cost function. The choice of this function is related to the type of learning (such as supervised learning, unsupervised learning, and enhanced learning) and the activation function.

Here, we detail two commonly used deep learning applications for psychiatric disorder diagnosis.

By leveraging a DNNs on the TensorFlow framework, Khan et al. [88] proposed a computational tool (integrated mental-disorder GEnome score, or iMEGES) to analyze the whole genome/exome sequencing data on personal genomes. Based on the deep learning framework, this tool creates prioritized gene scores for psychiatric disorders [89]. The findings revealed that the property of this tool are better than that of competing approaches when a large training dataset is available.

In addition, Heinsfeld et al. [39] applied deep learning algorithms on a large brain imaging dataset in order to identify patients with autism spectrum disorder based solely on the patients' brain activation patterns. The findings revealed that 70% accuracy was achieved in the dataset, and that deep learning methods can classify large datasets better than other methods. Furthermore, the results showed the promise of deep learning for clinical datasets and illustrated the future application of AI in the identification of mental disorders.

Although extremely advanced performance has been demonstrated in several fields, deep learning has been under close concern for its lack of transparency during the learning and testing processes [90–92]. For example, deep learning has been referred to as a "black box". In comparison, techniques such as LR are simple and easy to understand.

For this reason, recent endeavors in interpretable DNNs are introduced here. For example, in terms of CNN visualization, Springenberg et al. [93] proposed a deconvolution approach that can be used to acquire features from deep learning. Kindermans et al. [94] proposed a method to visualize the regions in the input image that contribute most to the CNN decision-making process. In a study on interpreting neural networks with traditional machine learning models, Zhang et al. [95] proposed a method to interpret the convolution layer characteristics of pretrained CNNs, and used an explanatory graph to reveal the knowledge level hidden in the CNN. In short, a good AI model should be interpretable, generalizable, and more adaptive, and should learn from data, rules, and interactions.

4. Discussion

Considering the interaction between the environment and multiple susceptibility genes, the process of diagnosing psychiatric disorders is described as follows: first, micromolecular variations [96,97], such as protein expression [98,99], are investigated by EEG; second, changes in brain structure, specific neural circuits, and brain function are examined by MRI; and finally, when patients have clinical phenotype switches, kinesics data is used to identify behavioral changes [100]. In particular, the discovery of these changes at the structural, functional, and behavioral levels can not only help in diagnosing psychiatric disorders at an early stage, but also assist in exploring the key biomarkers for diagnosing psychiatric disorders.

However, the clinical symptoms of psychiatric disorders are complex and diverse. Diagnosing psychiatric disorders is one of the more labor-intensive tasks in medicine, and thus precisely falls within the area of machine learning. The general medical system cannot always accurately and rapidly diagnose patients. The continuous development of clinical examination technology and AI technology can not only greatly reduce costs, but also obtain assistant diagnosis results in real time. AI can help doctors to provide more accurate and efficient diagnoses [101–103], thus improving the level of clinical diagnoses of neuropsychiatric diseases.

The typical application of AI in this context is in diagnosing diseases based on DNNs [104]. DNNs can accurately predict the risk of disease or abnormal lesions through a deep learning model based on the relevant disease data. In the literature, although the analytic performance of deep learning for diagnosing psychiatric disorders is better, there are also some problems, such as: ① higher requirements for computer configurations; ② higher requirements for data quantity (the experimental performance is better only when there is more data); and ③ more time being consumed by experiments. These problems are worthy of further study and discussion in the future.

In short, although AI has made great progress in diagnosing psychiatric disorders, there are still many research areas for the improvement of AI-based applications [105]. First, since current research is based on classic shallow learning algorithms, it is difficult to share and use information among high-dimensional features. Thus, deep learning is a future study direction. Second, it is necessary to employ unsupervised learning to perform automatic annotation for unlabeled psychiatric disorder imaging data. Finally, because the current AI-based model can only process homologous datasets, its generalizability is insufficient. Therefore, migration learning, multi-view learning, and ensemble learning [106] will be used to process big psychiatric disorder data in the distant future.

5. Conclusion

At present, MRI, EEG, and kinesics are important methods and references in the diagnosis of psychiatric disorders. With the application of AI technologies in medicine becoming increasingly widespread, traditional artificial diagnostic methods are gradually being eliminated, while the role of MRI, EEG, and kinesics in computer-aided diagnosis methods is becoming increasingly important. Therefore, this study mainly reviewed the application of MRI, EEG, and kinesics by providing the following: ① a brief introduction of the process of psychiatric disorder diagnosis and an analysis of the main data types generated therein; ② an introduction of the important role of AI technology in the diagnosis of psychiatric disorders, and its application performance; and ③ a summary and analysis of the methods proposed for diagnosing diseases based on the current hot topic of deep learning.

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Compliance with ethics guidelines

Guang-Di Liu, Yu-Chen Li, Wei Zhang, and Le Zhang declare that they have no conflict of interest or financial conflicts to disclose.

References

[1] Walker ER, McGee RE, Druss BG. Mortality in mental disorders and global disease burden implications: a systematic review and meta-analysis. JAMA Psychiatry 2015;72(4):334–41.
[2] GBD 2017 DALYs and HALE Collaborators. Global, regional, and national disability-adjusted life-years (DALYs) for 359 diseases and injuries and healthy life expectancy (HALE) for 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. Lancet 2018;392(10159):1859–922.
[3] The US Burden of Disease Collaborators. The state of US health, 1990–2016: burden of diseases, injuries, and risk factors among US states. JAMA 2018;319(14):1444–72.
[4] Rose N. The Human Brain Project: social and ethical challenges. Neuron 2014;82(6):1212–5.
[5] Iritani S, Habuchi C, Sekiguchi H, Torii Y. Brain research and clinical psychiatry: establishment of a psychiatry brain bank in Japan. Nagoya J Med Sci 2018;80(3):309–15.
[6] Poo MM, Du JL, Ip NY, Xiong ZQ, Xu B, Tan T. China Brain Project: basic neuroscience, brain diseases, and brain-inspired computing. Neuron 2016;92(3):591–6.
[7] Insel TR. The NIMH Research Domain Criteria (RDoC) project: precision medicine for paychiatry. Am J Psychiatry 2014;171(4):395–7.
[8] Kalmady SV, Greiner R, Agrawal R, Shivakumar V, Narayanaswamy JC, Brown MRG, et al. Towards artificial intelligence in mental health by improving schizophrenia prediction with multiple brain parcellation ensemble-learning. NPJ Schizophr 2019;5:2.
[9] Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, et al. A guide to deep learning in healthcare. Nat Med 2019;25:24–9.
[10] Dwyer DB, Falkai P, Koutsouleris N. Machine learning approaches for clinical psychology and psychiatry. Annu Rev Clin Psychol 2018;14:91–118.
[11] Sarma GP, Hay NJ, Safron A. AI safety and reproducibility: establishing robust foundations for the neuropsychology of human values. In: Gallina B, Skavhaug A, Schoitsch E, Bitsch F, editors. SAFECOMP 2018: computer safety, reliability, and security; 2018 Sep 18–21; Västerås, Sweden. Cham: Springer; 2018. p. 507–12.
[12] Stead WW. Clinical implications and challenges of artificial intelligence and deep learning. JAMA 2018;320(11):1107–8.
[13] Gao H, Yin Z, Cao Z, Zhang L. Developing an agent-based drug model to investigate the synergistic effects of drug combinations. Molecules 2017;22(12):2209.
[14] Xia Y, Yang CW, Hu N, Yang ZZ, He XY, Li TT, et al. Exploring the key genes and signaling transduction pathways related to the survival time of glioblastoma multiforme patients by a novel survival analysis model. BMC Genomics 2017;18:950.
[15] Zhang L, Xiao M, Zhou JS, Yu J. Lineage-associated underrepresented permutations (LAUPs) of mammalian genomic sequences based on a Jellyfish-based LAUPs analysis application (JBLA). Bioinformatics 2018;34(21):3624–30.
[16] Jan A, Meng HY, Gaus YFBA, Zhang F. Artificial intelligent system for automatic depression level analysis through visual and vocal expressions. IEEE Trans Cogn Dev Syst 2018;10(3):668–80.
[17] Wen HW, Liu Y, Wang SP, Li ZY, Zhang JS, Peng Y, et al. Multi-threshold white matter structural networks fusion for accurate diagnosis of early Tourette syndrome children. In: Armato SG, Petrick NA, editors. Medical Imaging 2017: Computer-Aided Diagnosis; 2017 Feb 11–16; Orlando, FL, USA. Bellingham: SPIE; 2017. p. 10134 1Q.
[18] Li T, Cheng Z, Zhang L. Developing a novel parameter estimation method for agent-based model in immune system simulation under the framework of history matching: a case study on influenza a virus infection. Int J Mol Sci 2017;18(12):2592.
[19] Peng H, Peng T, Wen J, Engler DA, Matsunami RK, Su J, et al. Characterization of p38 MAPK isoforms for drug resistance study using systems biology approach. Bioinformatics 2014;30(13):1899–907.
[20] Luxton DD, editor. Artificial intelligence in behavioral and mental health care. London: Academic Press; 2015.
[21] Wallace R. Embodied cognition and its disorders. In: Wallace R, editor. Computational psychiatry. New York: Springer; 2017. p. 129–52.
[22] Rosen BR, Huang SY, Stufflebeam SM. Pushing the limits of human neuroimaging. JAMA 2015;314(10):993–4.
[23] Hategan A, Bourgeois JA, Cheng T, Young J. Neuropsychology and neuroimaging in clinical geriatric psychiatry. In: Hategan A, Bourgeois JA, Cheng T, Young J, editors. Geriatric psychiatry study guide. Cham: Springer; 2018. p. 23–38.
[24] Park MTM, Raznahan A, Shaw P, Gogtay N, Lerch JP, Chakravarty MM. Neuroanatomical phenotypes in mental illness: identifying convergent and divergent cortical phenotypes across autism, ADHD and schizophrenia. J Psychiatry Neurosci 2018;43(3):201–12.
[25] Wintermark M, Colen R, Whitlow CT, Zaharchuk G. The vast potential and bright future of neuroimaging. Br J Radiol 2018;91(1087):20170505.
[26] Webb S. Deep learning for biology. Nature 2018;554(7693):555–7.
[27] Böhle M, Eitel F, Weygandt M, Ritter K. Visualizing evidence for Alzheimer's disease in deep neural networks trained on structural MRI data. 2019. arXiv:1903.07317.
[28] Carin L, Pencina MJ. On deep learning for medical image analysis. JAMA 2018;320(11):1192–3.
[29] Wolfers T, Buitelaar JK, Beckmann CF, Franke B, Marquand AF. From estimating activation locality to predicting disorder: a review of pattern recognition for neuroimaging-based psychiatric diagnostics. Neurosci Biobehav Rev 2015;57:328–49.
[30] Arbabshirani MR, Plis S, Sui J, Calhoun VD. Single subject prediction of brain disorders in neuroimaging: promises and pitfalls. Neuroimage 2017;145(Pt B):137–65.
[31] Vieira S, Pinaya WHL, Mechelli A. Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: methods and applications. Neurosci Biobehav Rev 2017;74(Pt A):58–75.
[32] Bengio Y. Learning deep architectures for AI. Hanover: Now Publishers Inc.; 2009.
[33] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;521(7553):436–44.
[34] Calhoun VD, Sui J. Multimodal fusion of brain imaging data: a key to finding the missing link(s) in complex mental illness. Biol Psychiatry Cogn Neurosci Neuroimaging 2016;1(3):230–44.
[35] Plis SM, Hjelm DR, Salakhutdinov R, Allen EA, Bockholt HJ, Long JD, et al. Deep learning for neuroimaging: a validation study. Front Neurosci 2014;8:229.
[36] Payan A, Montana G. Predicting Alzheimer's disease: a neuroimaging study with 3D convolutional neural networks. 2015. arXiv:1502.02506.
[37] Hosseini-Asl E, Ghazal M, Mahmoud A, Aslantas A, Shalaby AM, Casanova MF, et al. Alzheimer's disease diagnostics by a 3D deeply supervised adaptable convolutional network. Front Biosci 2018;23:584–96.
[38] Koyamada S, Shikauchi Y, Nakae K, Koyama M, Ishii S. Deep learning of fMRI big data: a novel approach to subject-transfer decoding. 2015. arXiv:1502.00093.
[39] Heinsfeld AS, Franco AR, Craddock RC, Buchweitz A, Meneguzzi F. Identification of autism spectrum disorder using deep learning and the ABIDE dataset. Neuroimage Clin 2018;17:16–23.
[40] Grotegerd D, Suslow T, Bauer J, Ohrmann P, Arolt V, Stuhrmann A, et al. Discriminating unipolar and bipolar depression by means of fMRI and pattern classification: a pilot study. Eur Arch Psychiatry Clin Neurosci 2013;263(2):119–31.
[41] Kermany DS, Goldbaum M, Cai W, Valentim CCS, Liang H, Baxter SL, et al. Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell 2018;172(5):1122.
[42] Hannesdóttir DK, Doxie J, Bell MA, Ollendick TH, Wolfe CD. A longitudinal study of emotion regulation and anxiety in middle childhood: associations with frontal EEG asymmetry in early childhood. Dev Psychobiol 2010;52(2):197–204.
[43] Avram J, Balteş FR, Miclea M, Miu AC. Frontal EEG activation asymmetry reflects cognitive biases in anxiety: evidence from an emotional face Stroop task. Appl Psychophysiol Biofeedback 2010;35(4):285–92.
[44] Thibodeau R, Jorgensen RS, Kim S. Depression, anxiety, and resting frontal EEG asymmetry: a meta-analytic review. J Abnorm Psychol 2006;115(4):715–29.
[45] Hosseinifard B, Moradi MH, Rostami R. Classifying depression patients and normal subjects using machine learning techniques and nonlinear features from EEG signal. Comput Methods Programs Biomed 2013;109(3):339–45.
[46] Field T, Diego M. Maternal depression effects on infant frontal EEG asymmetry. Int J Neurosci 2008;118(8):1081–108.
[47] Iosifescu DV, Greenwald S, Devlin P, Mischoulon D, Denninger JW, Alpert JE, et al. Frontal EEG predictors of treatment outcome in major depressive disorder. Eur Neuropsychopharmacol 2009;19(11):772–7.
[48] Bisch J, Kreifelts B, Bretscher J, Wildgruber D, Fallgatter A, Ethofer T. Emotion perception in adult attention-deficit hyperactivity disorder. J Neural Transm 2016;123(8):961–70.

Please cite this article as: G.-D. Liu, Y. C. Li, W. Zhang et al., A Brief Review of Artificial Intelligence Applications and Algorithms for Psychiatric Disorders, Engineering, https://doi.org/10.1016/j.eng.2019.06.008

[49] Lopez-Duran NL, Kuhlman KR, George C, Kovacs M. Facial emotion expression recognition by children at familial risk for depression: high-risk boys are oversensitive to sadness. J Child Psychol Psychiatry 2013;54(5):565–74.
[50] Ooi KEB, Lech M, Allen NB. Multichannel weighted speech classification system for prediction of major depression in adolescents. IEEE Trans Biomed Eng 2013;60(2):497–506.
[51] Scherer S, Stratou G, Mahmoud M, Boberg J, Gratch J, Rizzo A, et al. Automatic behavior descriptors for psychological disorder analysis. Proceedings of 2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition; 2013 Apr 22–26; Shanghai, China. Piscataway: IEEE; 2013.
[52] Girard JM, Cohn JF, Mahoor MH, Mavadati S, Rosenwald DP. Social risk and depression: evidence from manual and automatic facial expression analysis. Proceedings of 2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition; 2013 Apr 22–26; Shanghai, China. Piscataway: IEEE; 2013.
[53] Wang P, Barrett F, Martin E, Milonova M, Gur RE, Gur RC, et al. Automated video-based facial expression analysis of neuropsychiatric disorders. J Neurosci Methods 2008;168(1):224–38.
[54] Zhu Y, Shang Y, Shao Z, Guo G. Automated depression diagnosis based on deep networks to encode facial appearance and dynamics. IEEE Trans Affect Comput 2018;9(4):578–84.
[55] Kaletsch M, Pilgramm S, Bischoff M, Kindermann S, Sauerbier I, Stark R, et al. Major depressive disorder alters perception of emotional body movements. Front Psychiatry 2014;5:4.
[56] Dhamecha TI, Singh R, Vatsa M, Kumar A. Recognizing disguised faces: human and machine evaluation. PLoS ONE 2014;9(7):e99212.
[57] Li M, Xu H, Liu X, Lu S. Emotion recognition from multichannel EEG signals using *k*-nearest neighbor classification. Technol Health Care 2018;26(Suppl 1):509–19.
[58] Righi G, Peissig JJ, Tarr MJ. Recognizing disguised faces. Vis Cogn 2012;20 (2):143–69.
[59] Gelman A, Carlin JB, Stern HS, Dunson DB, Vehtari A, Rubin DB. Bayesian data analysis. 3rd ed. Boca Raton: CRC Press; 2014.
[60] Tsigelny IF. Artificial intelligence in drug combination therapy. Brief Bioinform 2018 [Epub 2018 Feb 9].
[61] Zhang L, Bai W, Yuan N, Du Z. Comprehensively benchmarking applications for detecting copy number variation. PLoS Comput Biol 2019;15(5): e1007069.
[62] Glick M, Jenkins JL, Nettles JH, Hitchings H, Davies JW. Enrichment of high-throughput screening data with increasing levels of noise using support vector machines, recursive partitioning, and Laplacian-modified naive Bayesian classifiers. J Chem Inf Model 2006;46(1):193–200.
[63] Ferrante M, Redish AD, Oquendo MA, Averbeck BB, Kinnane ME, Gordon JA. Computational psychiatry: a report from the 2017 NIMH workshop on opportunities and challenges. Mol Psychiatry 2019;24:479–83.
[64] Friston KJ, Redish AD, Gordon JA. Computational nosology and precision psychiatry. Compr Psychiatry 2017;1:2–23.
[65] Anticevic A, Murray JD, editors. Computational psychiatry: mathematical modeling of mental illness. London: Academic Press; 2017.
[66] Grove TB, Yao B, Mueller SA, McLaughlin M, Ellingrod VL, McInnis MG, et al. A Bayesian model comparison approach to test the specificity of visual integration impairment in schizophrenia or psychosis. Psychiatry Res 2018;265:271–8.
[67] Hosmer Jr DW, Lemeshow S, Sturdivant RX. Applied logistic regression. 3rd ed. Toronto: John Wiley & Sons, Inc.; 2013.
[68] Pregibon D. Logistic regression diagnostics. Ann Stat 1981;9(4):705–24.
[69] Ng A. CS229 Lecture notes: Part II. 2000.
[70] Hagen E, Sømhovd M, Hesse M, Arnevik EA, Erga AH. Measuring cognitive impairment in young adults with polysubstance use disorder with MoCA or BRIEF-A—the significance of psychiatric symptoms. J Subst Abuse Treat 2019;97:21–7.
[71] Barker LC, Gruneir A, Fung K, Herrmann N, Kurdyak P, Lin E, et al. Predicting psychiatric readmission: sex-specific models to predict 30-day readmission following acute psychiatric hospitalization. Soc Psychiatry Psychiatr Epidemiol 2018;53(2):139–49.
[72] Shen CC, Hu LY, Tsai SJ, Yang AC, Chen PM, Hu YH. Risk stratification for the early diagnosis of borderline personality disorder using psychiatric co–morbidities. Early Interv Psychiatry 2018;12(4):605–12.
[73] Zhang L, Li J, Yin K, Jiang Z, Li T, Hu R, et al. Computed tomography angiography-based analysis of high-risk intracerebral haemorrhage patients by employing a mathematical model. BMC Bioinform 2019;20(Suppl 7):193.
[74] Su J, Zhang H. A fast decision tree learning algorithm. In: Proceedings of the 21st National Conference on Artificial Intelligence; 2006 Jul 16–20; Boston, MA, USA. Palo Alto. AAAI Press; 2006. p. 500–5.
[75] Nowozin S. Improved information gain estimates for decision tree induction. 2012. arXiv:1206.4620.
[76] Quinlan JR. Induction of decision trees. Mach Learn 1986;1(1):81–106.
[77] Carpenter KLH, Sprechmann P, Calderbank R, Sapiro G, Egger HL. Quantifying risk for anxiety disorders in preschool children: a machine learning approach. PLoS ONE 2016;11(11):e0165524.
[78] Sattler AF, Whiteside SPH, Bentley JP, Young J. Development and validation of a brief screening procedure for pediatric obsessive-compulsive disorder derived from the Spence Children's Anxiety Scale. J Obsessive Compuls Relat Disord 2018;16:29–35.
[79] Doshi AA, Sevugan P, Swarnalatha P. Modified support vector machine algorithm to reduce misclassification and optimizing time complexity. In: Swarnalatha P, Sevugan P, editors. Big data analytics for satellite image processing and remote sensing. Hershey: IGI Global; 2018. p. 34–56.
[80] Peng Z, Hu Q, Dang J. Multi-kernel SVM based depression recognition using social media data. Int J Mach Learn Cybern 2019;10(1):43–57.
[81] Al-Shargie F, Tang TB, Badruddin N, Kiguchi M. Towards multilevel mental stress assessment using SVM with ECOC: an EEG approach. Med Biol Eng Comput 2018;56(1):125–36.
[82] Li J, Fu A, Zhang L. An overview of scoring functions used for protein-ligand interactions in molecular docking. Interdiscip Sci Comput Life Sci 2019;11 (2):320–8.
[83] Brown JM, Campbell JP, Beers A, Chang K, Ostmo S, Chan RVP, et al. Automated diagnosis of plus disease in retinopathy of prematurity using deep convolutional neural networks. JAMA Ophthalmol 2018;136(7):803–10.
[84] Hinton G. Deep learning—a technology with the potential to transform health care. JAMA 2018;320(11):1101–2.
[85] Patlatzoglou K, Chennu S, Boly M, Noirhomme Q, Bonhomme V, Brichant JF, et al. Deep neural networks for automatic classification of anesthetic-induced unconsciousness. In: Wang S, Yamamoto V, Su J, Yang Y, Jones E, Iasemidis L, editors. BI 2018: brain informatics; 2018 Dec 7–9; Arlington, TX, USA. Cham: Springer; 2018. p. 216–25.
[86] Riva-Posse P, Choi KS, Holtzheimer PE, Crowell AL, Garlow SJ, Rajendra JK, et al. A connectomic approach for subcallosal cingulate deep brain stimulation surgery: prospective targeting in treatment-resistant depression. Mol Psychiatry 2018;23:843–9.
[87] Sánchez I, Soriano-Mas C, Verdejo-García A, Cardoner N, Fernández-Aranda F, Menchón JM, et al. Analysis of feature importance in deep neural networks in psychiatric disorders using magnetic resonance imaging [presentation]. The 27th Annual Meeting of the International Society for Magnetic Resonance in Medicine; 2019 May 11–16; Montreal, QC, Canada, 2019.
[88] Khan A, Liu Q, Wang K. iMEGES: integrated mental-disorder GEnome score by deep neural network for prioritizing the susceptibility genes for mental disorders in personal genomes. BMC Bioinform 2018;19:501.
[89] Zhang QS, Zhu SC. Visual interpretability for deep learning:a survey. Front Inform Technol Electron 2018;19(1):27–39.
[90] Akbarian S, Liu C, Knowles JA, Vaccarino FM, Farnham PJ, Crawford GE, et al. The PsychENCODE project. Nat Neurosci 2015;18:1707–12.
[91] Alain G, Bengio Y. Understanding intermediate layers using linear classifier probes. 2018. arXiv: 1610.01644v4.
[92] Yosinski J, Clune J, Nguyen A, Fuchs T, Lipson H. Understanding neural networks through deep visualization. 2015. arXiv:1506.06579.
[93] Springenberg JT, Dosovitskiy A, Brox T, Riedmiller M. Striving for simplicity: the all convolutional net. 2014. arXiv:1412.6806.
[94] Kindermans PJ, Schütt KT, Alber M, Müller KR, Erhan D, Kim B, et al. Learning how to explain neural networks: PatternNet and PatternAttribution. 2017. arXiv:1705.05598.
[95] Zhang Q, Yang Y, Ma H, Wu YN. Interpreting CNNs via decision trees. In: Proceedings of 2019 IEEE Conference on Computer Vision and Pattern Recognition; 2019 Jun 16–20; Long Beach. p. 6261–70.
[96] Zhuang YT, Wu F, Chen C, Pan YH. Challenges and opportunities: from big data to knowledge in AI 2.0. Front Inform Technol Electron 2017;18(1):3–14.
[97] Price II WN, Cohen IG. Privacy in the age of medical big data. Nat Med 2019;25:37–43.
[98] Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med 2019;25:44–56.
[99] Zhang L, Liu Y, Wang M, Wu Z, Li N, Zhang J, et al. *EZH2*-, *CHD4*-, and *IDH*-linked epigenetic perturbation and its association with survival in glioma patients. J Mol Cell Biol 2017;9(6):477–88.
[100] Zhang L, Qiao M, Gao H, Hu B, Tan H, Zhou X, et al. Investigation of mechanism of bone regeneration in a porous biodegradable calcium phosphate (CaP) scaffold by a combination of a multi-scale agent-based model and experimental optimization/validation. Nanoscale 2016;8(31):14877–87.
[101] Zhang L, Tao W, Feng H, Chen Y. Transcriptional and genomic targets of neural stem cells for functional recovery after hemorrhagic stroke. Stem Cells Int 2017;2017:2412890.
[102] Zhang L, Zhang S. Using, game theory to investigate the epigenetic control mechanisms of embryo development: comment on: "Epigenetic game theory: how to compute the epigenetic control of maternal-to-zygotic transition" by Qian Wang, et al.. Phys Life Rev 2017;20:140–2.
[103] Jeffries J. Book review: psychopharmacology: Stahl's essential psychopharmacology: neuroscientific basic and practical applications. Third Edition. Can J Psychiatry 2011;56(5):312–3.
[104] Zhang L, Zheng C, Li T, Xing L, Zeng H, Li T, et al. Building up a robust risk mathematical platform to predict colorectal cancer. Complexity 2017;2017:8917258.
[105] Acharya UR, Oh SL, Hagiwara Y, Tan JH, Adeli H, Subha DP. Automated EEG-based screening of depression using deep convolutional neural network. Comput Methods Programs Biomed 2018;161:103–13.
[106] Durstewitz D, Koppe G, Meyer-Lindenberg A. Deep neural networks in psychiatry. Mol Psychiatry 2019 [Epub 2019 Feb 15].

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