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Review

The potential of machine learning in diagnosing neurological and psychiatric diseases: a review

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Abstract

Purpose of the study Artificial intelligence (AI) is rapidly transforming medical practice, from patient care to diagnosis and treatment personalization. With our work, we aim to explore the application of machine learning (ML) and deep learning (DL) algorithms in the diagnosis of neurological and psychiatric diseases, exploring into both the benefits and the challenges associated with these new technologies.

Findings The examined technologies have shown considerable success in early diagnosis, as well as in the identification of risk factors and symptom management for diseases such as Alzheimer's, Parkinson's and psychiatric disorders. These models could help improve diagnostic accuracy and enable a more personalized therapeutic approach by utilizing large datasets with information such as biomarkers and medical images. However, certain challenges persist, including concerns about data quality, patient privacy and the ethical implications of algorithmic decisions.

Summary Artificial intelligence-based diagnostic methods offer great potential to enhance early diagnosis and, consequently, the management of neurological and psychiatric disorders. To maximise their application, it is essential to ensure transparency and interpretability of the models, which are fundamental for their safe and effective use in medical practice.

Keywords Artificial intelligence · Machine learning · Deep learning · Diagnosis · Neurological diseases · Psychiatric disease

1 Introduction

The recent advent and rapid development of artificial intelligence (AI) are transforming medical practice. Similar to many other research fields, healthcare has witnessed unprecedented developments over the last decade. The ability to personalise patient care, assist clinicians in decision-making, and enhance treatment effectiveness are all areas in which artificial intelligence has demonstrated significant value [1, 2]. Specifically, machine learning enables the extraction of latent patterns directly from data, which are then used to make inferences. This approach is further enhanced by the vast amount of data produced by the healthcare systems, insurance companies and medical research institutions [3]. Access to this enormous amount of Big Data allows Artificial Intelligence tools to improve their performances in order to optimize the decision-making process, formulate early diagnoses and personalize treatment by predicting the possible outcome [4]. Beyond effectiveness, these methods also raise numerous ethical issues. Debates related to patient privacy, data security, accountability for decisions and respect for individual

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autonomy are emerging and are fundamental to the correct implementation of these technologies [5]. Thus, several new challenges must be addressed to facilitate the full integration of these technologies into the healthcare systems. For instance, the development of interpretable systems is fundamental: understanding how algorithms extract data and create outputs is crucial for the usability and acceptance of such tools [6].

Among all the possible tasks that AI can handle in medical practice, particular importance is given to its role in diagnosis. Machine learning and deep learning technologies have been employed for years to differentiate healthy subjects from patients or to predict the disease progression. This approach has found success in various branches of medicine, including oncology [7], neurology [8], radiology [9] and psychiatry [10]. In each case, algorithms handle data such as biomarkers [11] or medical scans [12], identifying hidden patterns to infer the patient's health status. Therefore, these tools are essential for obtaining a rapid and early diagnoses, ensuring unbiased decision-making and improving symptoms management. Regarding diagnostic accuracy, in recent years, several studies have compared AI to clinicians [13] [14]. For instance, Kim et al. (2020) [15] shows how their AI model is more sensitive than clinicians in diagnosing breast cancer with mammography (0.9 vs 0.78), even in the case of early breast cancer (0.91 vs 0.74). Again, Becker et al. (2022) [16] evaluated the ability of a deep learning model to identify pneumonia in chest radiographs and then compared it to the ability of two radiologists. As a result, AI outperformed the clinicians: the AI model's sensitivity and specificity were 95.4% and 66,0% respectively, while the clinicians achieved only 50,6% and 73%. Also, Esteva et al. (2017) [17] evaluates the performance of a CNN trained to classify skin cancer and compares it to two dermatologists. The AI model reaches an overall accuracy of 72.1 ± 0.9% with a three-class disease partition (versus 65.56% and 66.0% accuracy of the clinicians) and 55.4 ± 1.7% with a nine-class disease partition (versus 53.3% and 55.0%).

In recent years, huge strides in the use of artificial intelligence for diagnosis have been made in neurology and psychiatry, where many models have been developed with different goals. For instance, Badža et al. (2020) [12] proposes a new Convolutional Neural Network architecture to classify three brain tumor types: meningioma, glioma, and pituitary tumor. The tested model, trained using a database composed by T1-weighted contrast-enhanced MRI images, showed good generalisation capability and reduced execution speed, while maintaining a simple architecture. Regarding neurodegenerative disease detection, Gupta et al. (2023).[18] shows how AI can promote Parkinson's disease early diagnosis. Machine learning models have proven useful to identify diseased patients using different types of data. Speech recordings can be used to automatically discover vocal issues, while handwriting characteristics are used to identify bradykinetic movements and movement control. At the same time, gait data have been used to differentiate between healthy controls and Parkinson's individuals. Finally, another source of data useful for this task are imaging scans, where machine leaning models can automatically find abnormalities in the scans to diagnose Parkinson's disease. AI has proven useful also in other neurological pathologies diagnosis, such as epilepsy. For instance, Yuan et al. (2018) [19] proposes a new method to automatically identify epileptic EEG signals. This procedure relies on both a Support Vector Machine classifier and Local Binary Pattern Operators and reaches high levels of recognition accuracy. Finally, AI has been used to identify psychiatric disorder subtypes. For instance, Zhang et al. (2021) [20] shows the identification of two clinically relevant subtypes of both post-traumatic stress disorder and major depressive disorder, discovered thanks to a machine learning procedure based on high-density resting-state electroencephalography.

In summary, this paper aims to investigate the current state of the literature on the use of machine learning and deep learning algorithms in the diagnosis of both neurological and psychiatric diseases. We will highlight from the existing literature the benefits and the challenges associated with these methodologies, examining into the most relevant approaches and analysing the most used algorithms and metrics, starting from the most cited case studies.

The paper is structured as follows (Fig. 1): Sect. 1 offers a general overview of the use of machine learning algorithms to diagnose both neurological and psychiatric diseases. Section 2 contains a brief and general introduction to the concepts of machine learning and deep learning. Section 3 reviews the most significant existing literature on this topic. Not all the papers analysed in this section have purposes similar to ours, but they still offer an in-depth analysis of the pros and cons of using artificial intelligence in diagnosis. In Sect. 4 we outline the methodological criteria that guided the construction of the dataset and the formulation of the research questions. Section 5 presents the results of our analysis, addressing the first four research questions. Section 6 corresponds to the analysis of the ten most cited papers. In this section we will explore: the most used algorithms, which metrics have been used to evaluate their performance, and which challenges have been addressed. In Sect. 7 we discuss the findings and present commentary on the results, while in Sect. 8 we outline potential limitations and future directions. Section 9 serves as a brief conclusion.

The need to develop this work arises from the growing incidence of neurological and psychiatric disorders worldwide, which in turn increases the urgent demand for accurate and timely diagnostic solutions. Current clinical approaches

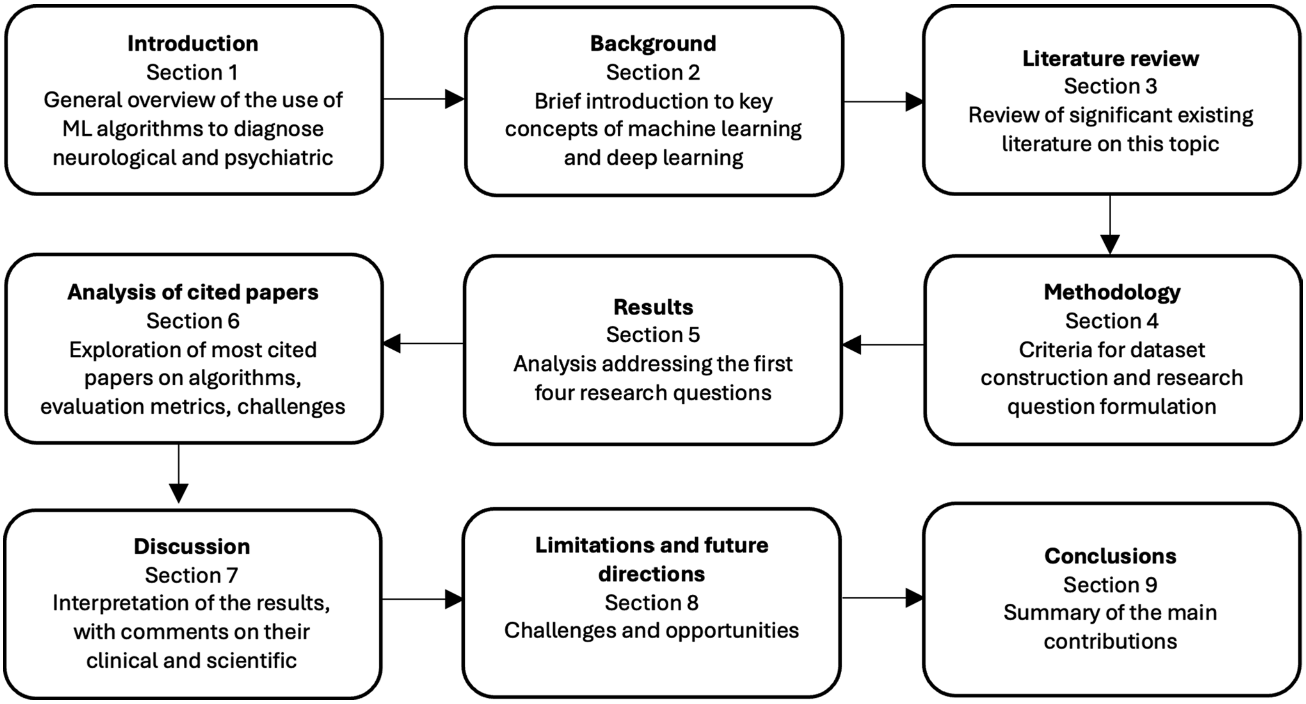

Fig. 1 Graphical Representation of the Article Index

are often imprecise and time-consuming. For this reason, we chose to highlight the potential of machine learning in enhancing diagnostic capabilities through the analysis of large-scale data. The main contributions of this work can be summarized in three key points: first, it provides an overview of recent applications of machine learning in the field of neurological and psychiatric disorders; second, it analyzes the performance and limitations of the various algorithms and data modalities used in these studies. Finally, it identifies the main challenges and future directions, serving as a guide for integrating ML tools into clinical practice. This study emphasises both the technical and clinical aspects of machine learning, offering a multidisciplinary perspective aimed to bridging the gap between data science and medicine.

2 Machine learning and deep learning

Before exploring into the use of AI-driven diagnostic methods in medicine, it is appropriate to explain the concepts underpinning our research. Machine learning is a discipline that arises from the intersection of statistics and computer science and deals with the study of how computers can learn directly from data, whether these data consist of numerical values or images. Through this process, algorithms can be trained to accomplish a variety of tasks. According to the type of training, ML can be categorised in supervised learning, unsupervised learning and reinforcement learning [21]. Supervised learning entails training an algorithm to produce a known output. This requires the use of "labelled" data, which include both the features and the correct outputs. In this way, the algorithm's performances can be verified by comparing the predicted output to the desired output, thus determining whether further training is necessary. Supervised learning is particularly useful to make inferences about new, unseen data, thanks to the knowledge gained in the training phase [22]. Conversely, unsupervised learning involves training the system on unlabelled data. This enables the model to uncover latent patterns within raw data without the need for explicit instruction [23]. Lastly, reinforcement learning represents a hybrid approach, utilising a reward-and-punishment mechanism. Based on the accuracy of its outputs, the model is rewarded or punished in order to optimize future inferences. Thanks to the feedback it receives, the model improves its performances, providing more accurate outputs [24]. Machine learning algorithms can be employed for both classification and prediction tasks and, depending on the task they were trained for, they have proven useful across various objectives. Over time, numerous machine learning algorithms have been developed, each with distinct mechanisms. Linear regression, logistic regression, decision trees, support vector machines (SVM) and K-nearest neighbors (KNN) are among the most widely used algorithms, which will be examined in greater detail in Sect. 6 [25].

Deep learning, a specialised subset of machine learning, utilises artificial neural networks (NN) to handle data, identify complex patterns and make predictions. A deep neural network (DNN) comprises multiple layers, each of which work on the representations it receives from the preceding layer and transforms them before passing the output to the next layer. Each layer consists of a set of nodes, which function as basic processing units inspired by biological neurons. Data processing starts at the input layer and propagates forward through subsequent layers. Adjustable parameters, referred to as "weights", are applied to the input at each layer and are subjected to activation functions that introduce non-linearities. In this way the network can progressively process at a higher level of complexity and abstraction. To ensure accuracy and enhance network performance, the output created by the network is compared against the desired output, and the error is calculated using a loss function. A reduction in the loss function corresponds to improved output accuracy. To achieve this, the error is propagated backwards through the layers, where the weights are adjusted. This iterative procedure is repeated until the desired performance level is attained [26]. The ability to modify their architecture and parameters, coupled with their high effectiveness, has rendered neural networks exceptionally useful for executing complex tasks by processing vast quantities of raw data. Their adaptability and performance have solidified their role as indispensable tools in addressing challenging problems across numerous domains.

3 Related works

In the existing literature, several reviews already address the implementation of AI tools for the diagnosis of both neurological and psychiatric disorders. While these were not included in our analysis, this section offers a general overview of the most relevant reviews.

Dwyer et al. (2018) [10] explores the potential future developments facilitated by the implementation of AI in the diagnosis, prognosis and treatment of psychiatric disorder. This integration has the potential to optimise diagnostic processes, increase the generalizability of results and reduce decision-making time. Furthermore, ML autonomously learns methods and parameters, leading to unbiased and highly generalizable results. Consequently, the limitations inherent in traditional statistical methods are avoided. However, the authors highlight that this approach also has its own limitations that must be addressed in the future: from the algorithms' explainability to the ethical implications related to their clinical implementation, from the validity of existing diagnostic and prognostic labels to the importance of using training data that are truly representative of the population.

Regarding the implementation of AI in psychiatry, Bzdok et al. (2017) [27] focuses on a different aspect: machine learning algorithms allow treatment predictions to be extrapolated directly from data. Rather than relying on pre-defined disease categories and hypotheses, these new methods are completely data-driven and can outperform conventional statistical techniques. In this way, a truly personalised and specialised medicine can be built, based on individual-level data, rather than group-level statistics that require formal hypothesis testing. More deeply, psychiatric disorders involve complex mechanisms ranging from molecular to social factors, making it challenging to formulate comprehensive hypotheses. ML, however, can detect disease-specific biological patterns, providing an opportunity to better address pathologies which are rooted both into genetics and life experiences.

Shatte et al. (2019) [28] present a broad overview of machine learning applications in mental health, focusing on a practical point of view. The results obtained demonstrate that AI can be applied across four domains: diagnosis, prognosis and treatment, public health, and research. In particular, the literature focuses predominantly on diagnosis, with more emphasis on depression, Alzheimer's syndrome and schizophrenia. However, it is highlighted how other pathologies and other areas are less explored. Overall, ML techniques have proven extremely effective in improving clinical and research processes. Among these, classification techniques, particularly for diagnostic purposes, are the most explored, while new unsupervised techniques have not yet been fully investigated.

Low et al. (2019) [29] focuses on the possibility of introducing speech processing technologies to improve the diagnosis and treatment of mental illnesses. Currently, diagnostic methods rely on the evaluation of patient reports, which can be influenced by subjective biases, cognitive deficits and social stigma. However, emerging technologies, including ML algorithms, allow to extrapolate behavioral and biological data in an unbiased manner, improving the objectivity of psychiatric assessment. This review synthesises findings from studies that employ automatically extracted acoustic features to detect psychiatric disorders and try to identify acoustic features that significantly differ in psychiatric disorder compared to neurotypical populations, linking them to the symptoms. Furthermore, it offers guidelines for data acquisition and modeling to enhance reproducibility and generalizability of results.

Focusing on the case of depression, Gao et al. (2018) [30] examines ML-based classification and prediction studies of major depression disorder (MDD) using features derived from MRI data. Altered brain networks can thus be utilised to discriminate patients from healthy individuals and to predict the outcomes of every possible treatment. Despite its promise, this approach faces challenges: the small sample sizes, the high feature dimensionality and the risk of overfitting the data.

There are many other studies addressing the application of ML not only in mental health, but also in diagnosing neurological disorders.

For instance, Raghavendra et al. (2019) [31] reviews the most widespread machine learning methods for the diagnosis of five neurological diseases: epilepsy, Parkinson's disease, Alzheimer's disease, multiple sclerosis, and ischemic brain stroke. The authors highlight the increasing prevalence of computer-aided diagnosis (CAD) systems in clinical practice which support clinicians in diagnostic and decision-making processes.

Myszczynska et al. (2020) [32] highlights the importance of utilising ML in diagnosing and treating neurodegenerative disorders. Unlike human analysts, algorithms can detect patterns and make inferences from multidimensional data. This enables early diagnoses from neuroimaging data, motor degeneration metrics and genetic analyses. On the other hand, the authors highlight how these new methods can also be used to develop new and effective therapies.

Battineni et al. (2020) [33] discusses the slow progression of chronic diseases and the resulting need for early diagnosis, in which artificial intelligence can be a valuable tool. By identifying the correct decision model, it is possible to diagnose chronic diseases and predict patient outcomes. ML predictive models are widely utilised in disease diagnosis; however, there is no standard method to define the best approach in clinical practice. Among the models considered are support vector machines (SVM), logistic regression (LR), and clustering. These models are expected to become increasingly valuable in future clinical practice, aiding decision-making and autonomous diagnoses in accordance with established regulations. Specifically, in nervous system disorders, the linear regression model has achieved an accuracy between 72 and 80% in identifying the causes of depression.

Finally, Shoeibi et al. (2021) [34] reviews methods used for automatic epileptic seizure detection through DL techniques. Since 2016, this research field has seen a significant increase, utilizing DL models such as convolutional neural networks (CNN), recurrent neural networks (RNN), deep belief networks (DBN), autoencoders (AE), CNN-RN and CNN-AE. Among these, CNNs are employed for disease diagnosis using biological signals, thanks to their mono or bidimensional architectures. In particular, 2D-CNN and 1D-CNN models are the most widely used for epileptic seizure detection. Recently, a novel 2D-CNN model was developed, capable of extracting both spectral and temporal features of EEG signals to learn the general structure of seizures [35]. However, it is not possible to identify a DL model superior to others for epileptic seizure detection. Thus, the structure must be chosen based on the dataset and the characteristics of the problem.

4 Research methodology

This section outlines the research methodology employed in this study, divided into five main phases, which can be summarized as follows: (4.1) formulation of research questions, (4.2) data source and search strategy, definition of (4.3) inclusion and (4.4) exclusion criteria, (4.5) data preprocessing, (4.6) data analysis and visualization, and (4.7) evaluation of performance metrics.

5 Research questions

First, the research questions that this paper aims to answer were defined:

RQ1 How many scientific studies have been published between 2018 and 2024 regarding the use of AI-driven diagnostic methods?

Objective: to determine the volume of research and analyse the evolution of studies on ML diagnostic algorithms.

RQ2 What are the most relevant research centers for studies on AI for the diagnosis of mental and neurological disorders?

Objective: to identify the primary sources of publication in this field.

RQ3 Which countries had the most active research centers?

Objective: to map the geographical distributions of research activity.

RQ4 In which disorder is AI most commonly applied
Objective: to identify the primary disorder where AI is frequently utilised.

RQ5 Which AI algorithms have been most commonly used to diagnose both neurological and mental disorders?

Objective: to analyse the predominant algorithms applied in this research field.

RQ6 What metrics were used to evaluate performance of the identified AI tools?

Objective: to determine the criteria used to measure the effectiveness and efficiency of the most commonly used AI tools.

RQ7 What challenges have been addressed in the development and implementation of AI-driven diagnostic methods?

Objective: to examine the practical, ethical and technical challenges faced in the field, with particular attention to issues of privacy, security and acceptance by patients and professionals.

5.1 Data source and search strategy

Scopus, a comprehensive citation database developed by Elsevier, was utilised for the preliminary analysis. Scopus provides access to peer-reviewed scientific outputs, with over 70 million bibliographic citations, abstracts, and bibliometric data across a wide range of academic disciplines, including natural sciences, engineering, medicine, social sciences, arts and humanities. It offers tools for analysing research trends, citations and academic collaborations, including metrics such as the h-index for quantifying the impact of authors. and their publications.

Furthermore, we exported Scopus citations to VOS viewer, a bibliography management software, for further analysis.

To narrow the search to our fields of interest, we applied the following search query in the Scopus database:

("artificial intelligence" OR "machine learning" OR "deep learning") AND ("diagnosis") AND ("psychiatric disorders" OR "psychopathology" OR “neurological disorders"). The search yielded 1,245 articles. To refine the results, the following inclusion and exclusion criteria were applied:

5.2 Inclusion criteria

- Papers published between 2014 and 2024.
- Written in English.
- Focused on the application of AI diagnosis
- Peer-reviewed journal articles.
- For duplicate articles, the most recent version was included.

5.3 Exclusion criteria

- Non-journal articles.
- Duplicates where an older version existed.

After applying these criteria, the dataset was reduced to 651, covering various research fields. Figure 2 shows the distribution of the total material across subject areas. Subsequently, only articles related to the medical field were selected, resulting in a final database of 265 documents (Table 1).

From this refined dataset, the 10 most cited papers were identified for an in-depth analysis aimed at addressing the last 3 research questions.

Table 1 Complete table of the 265 papers belonging to the original database:

Authors	Title	Journal	Year
Krishnan P.T.; Erramchetty S.K.; Balusa B.C	Advanced framework for epilepsy detection through image-based EEG signal analysis	Frontiers in Human Neuroscience	2024
Parvin S.; Nimmy S.F.; Kamal M.S	Convolutional neural network based data interpretable framework for Alzheimer's treatment planning	Visual Computing for Industry, Biomedicine, and Art	2024
Bertl M.; Bignoumba N.; Ross P.; Yahia S.B.; Draheim D	Evaluation of deep learning-based depression detection using medical claims data	Artificial Intelligence in Medicine	2024
Chen H.; Lei Y.; Li R.; Xia X.; Cui N.; Chen X.; Liu J.; Tang H.; Zhou J.; Huang Y.; Tian Y.; Wang X.; Zhou J	Resting-state EEG dynamic functional connectivity distinguishes non-psychotic major depression, psychotic major depression and schizophrenia	Molecular Psychiatry	2024
Mohd Salah Aljabiri S.; Hamdan M.M	Analyzing lower body movements using machine learning to classify autistic children	Biomedical Signal Processing and Control	2024
Leonardsen E.H.; Persson K.; Grødem E.; Dinsdale N.; Schellhorn T.; Roe J.M.; Vidal-Piñeiro D.; Sørensen Ø.; Kaufmann T.; Westman E.; Marquand A.; Selbæk G.; Andreassen O.A.; Wolfers T.; Westlye L.T.; Wang Y	Constructing personalized characterizations of structural brain aberrations in patients with dementia using explainable artificial intelligence	npj Digital Medicine	2024
Strigo I.A.; Kadlec M.; Mitchell J.M.; Simmons A.N	Identification of group differences in predictive anticipatory biasing of pain during uncertainty: preparing for the worst but hoping for the best	Pain	2024
Patel M.; Bhatt H.; Munshi M.; Pandya S.; Jain S.; Thakkar P.; Yoon S	CNN-FEBAC: A framework for attention measurement of autistic individuals	Biomedical Signal Processing and Control	2024
Li Y.; Shao Y.; Wang J.; Liu Y.; Yang Y.; Wang Z.; Xi Q	Machine learning based on functional and structural connectivity in mild cognitive impairment	Magnetic Resonance Imaging	2024
Li T.; Guo Y.; Zhao Z.; Chen M.; Lin Q.; Hu X.; Yao Z.; Hu B	Automated Diagnosis of Major Depressive Disorder With Multi-Modal MRIs Based on Contrastive Learning: A Few-Shot Study	IEEE Transactions on Neural Systems and Rehabilitation Engineering	2024
Ho C.S.H.; Wang J.; Tay G.W.N.; Ho R.; Husain S.F.; Chiang S.K.; Lin H.; Cheng X.; Li Z.; Chen N	Interpretable deep learning model for major depressive disorder assessment based on functional near-infrared spectroscopy	Asian Journal of Psychiatry	2024
He Z.; Yang J.; Alroobaea R.; Yee Por L	SeizureLSTM: An optimal attention-based trans-LSTM network for epileptic seizure detection using optimal weighted feature integration	Biomedical Signal Processing and Control	2024
Zadka A.; Rabin N.; Gazit E.; Mirelman A.; Nieuwboer A.; Rochester L.; Del Din S.; Pelosin E.; Avanzino L.; Bloem B.R.; Della Croce U.; Cereatti A.; Hausdorff J.M	A wearable sensor and machine learning estimate step length in older adults and patients with neurological disorders	npj Digital Medicine	2024
Child B.; Saywell I.; da Silva R.; Collins-Praino L.; Baetu I	Cognitive function in different motor subtypes of Parkinson's disease: A systematic review protocol	Health Science Reports	2024
Peng L.; Cai S.; Wu Z.; Shang H.; Zhu X.; Li X	MMGPL: Multimodal Medical Data Analysis with Graph Prompt Learning	Medical Image Analysis	2024

Table 1 (continued)

Authors	Title	Journal	Year
Ravan M.; Noroozi A.; Sanchez M.M.; Borden L.; Alam N.; Flor-Henry P.; Colic S.; Khodayari-Rostamabad A.; Minuzzi L.; Hasey G	Diagnostic deep learning algorithms that use resting EEG to distinguish major depressive disorder, bipolar disorder, and schizophrenia from each other and from healthy volunteers	Journal of Affective Disorders	2024
Zhang Y.; Xie R.; Beheshti I.; Liu X.; Zheng G.; Wang Y.; Zhang Z.; Zheng W.; Yao Z.; Hu B	Improving brain age prediction with anatomical feature attention-enhanced 3D-CNN	Computers in Biology and Medicine	2024
Stassen H.H.; Bachmann S.; Bridler R.; Cattapan K.; Hartmann A.M.; Rujescu D.; Seifritz E.; Weisbrod M.; Scharfetter C	Analysis of genetic diversity in patients with major psychiatric disorders versus healthy controls: A molecular-genetic study of 1698 subjects genotyped for 100 candidate genes (549 SNPs)	Psychiatry Research	2024
Jiang T.; Nagy D.; Rosellini A.J.; Horváth-Puhó E.; Keyes K.M.; Lash T.L.; Galea S.; Sørensen H.T.; Gradus J.L	Prediction of suicide attempts among persons with depression: a population-based case cohort study	American Journal of Epidemiology	2024
Puteikis K.; Mameniškienė R	Artificial intelligence: Can it help us better grasp the idea of epilepsy? An exploratory dialogue with ChatGPT and DALL·E 2	Epilepsy and Behavior	2024
Darvishi-Bayazi M.-J.; Ghaemi M.S.; Lesort T.; Arefin M.R.; Faubert J.; Rish I	Amplifying pathological detection in EEG signaling pathways through cross-dataset transfer learning	Computers in Biology and Medicine	2024
Shen J.; Xiao C.; Qiao X.; Zhu Q.; Yan H.; Pan J.; Feng Y	A diagnostic model based on bioinformatics and machine learning to differentiate bipolar disorder from schizophrenia and major depressive disorder	Schizophrenia	2024
Bakkialakshmi V.S.; Arulalan V.; Chinnaraju G.; Ghosh H.; Rahat I.S.; Saha A	Exploring the Potential of Deep Learning in the Classification and Early Detection of Parkinson's Disease	EAI Endorsed Transactions on Pervasive Health and Technology	2024
Ileșan R.R.; Ștefănigă S.-A.; Fleșar R.; Beyer M.; Ginghină E.; Peștean A.S.; Hirsch M.C.; Perju-Dumbravă L.; Faragó P	In Silico Decoding of Parkinson's: Speech & Writing Analysis	Journal of Clinical Medicine	2024
Grazioli S.; Crippa A.; Buo N.; Ceccarelli S.B.; Molteni M.; Nobile M.; Salandi A.; Trabattoni S.; Caselli G.; Colombo P	Use of Machine Learning Models to Differentiate Neurodevelopment Conditions Through Digitally Collected Data: Cross-Sectional Questionnaire Study	JMIR Formative Research	2024
Maruo T.; Takagi S.; Uchida S.; Takahashi H.; Sugihara G	Temporal patterns of sleep latency in central hypersomnia and attention deficit hyperactivity disorder: a cluster analysis exploration using Multiple Sleep Latency Test	Frontiers in Psychiatry	2024
Felix C.; Johnston J.D.; Owen K.; Shirima E.; Hinds S.R., II; Mandl K.D.; Milinovich A.; Alberts J.L	Explainable machine learning for predicting conversion to neurological disease: Results from 52,939 medical records	Digital Health	2024
Karaglani M.; Agorastos A.; Panagopoulou M.; Parlapani E.; Athanasis P.; Bitsios P.; Tzitzikou K.; Theodosiou T.; Iliopoulos I.; Bozikas V.-P.; Chatzaki E	A novel blood-based epigenetic biosignature in first-episode schizophrenia patients through automated machine learning	Translational Psychiatry	2024
Irfan M.; Shahrestani S.; Elkhodr M	Machine learning in neurological disorders: A multivariate LSTM and AdaBoost approach to Alzheimer's disease time series analysis	Health Care Science	2024
Wang G.; Fan F.; Shi S.; An S.; Cao X.; Ge W.; Yu F.; Wang Q.; Han X.; Tan S.; Tan Y.; Wang Z	Multi modality fusion transformer with spatio-temporal feature aggregation module for psychiatric disorder diagnosis	Computerized Medical Imaging and Graphics	2024

Table 1 (continued)

Authors	Title	Journal	Year
Hassouneh A.; Bazuin B.; Danna-Dos-Santos A.; Acar I.; Abdel-Qader I	Feature Importance Analysis and Machine Learning for Alzheimer's Disease Early Detection: Feature Fusion of the Hippocampus, Entorhinal Cortex, and Standardized Uptake Value Ratio	Digital Biomarkers	2024
Sumiyoshi T.; Campanella S.; Giordano G.M.; Ishii R.; Pogarell O	Understanding the Pathophysiology of Mental Diseases and Early Diagnosis Thanks to Electrophysiological Tools: Some Insights and Empirical Facts	Clinical EEG and Neuroscience	2024
Zhang D.; Duan C.; Anazodo U.; Wang Z.J.; Lou X	Self-supervised anatomical continuity enhancement network for 7 T SWI synthesis from 3 T SWI	Medical Image Analysis	2024
Hou R.; Guo Q.; Wu Q.; Zhao Z.; Hu X.; Yan Y.; He W.; Lyu P.; Su R.; Tan T.; Wang X.; Li Y.; He D.; Xu L	Quantification of Hypsarrhythmia in Infantile Spasmatic EEG: A Large Cohort Study	IEEE Transactions on Neural Systems and Rehabilitation Engineering	2024
Rini P.L.; Gayathri K.S	Revolutionizing dementia detection: Leveraging vision and Swin transformers for early diagnosis	American Journal of Medical Genetics, Part B: Neuropsychiatric Genetics	2024
Lin J.-W.; Fan Z.-C.; Tzou S.-C.; Wang L.-J.; Ko L.-W	Temporal Alpha Dissimilarity of ADHD Brain Network in Comparison With CPT and CATA	IEEE Transactions on Neural Systems and Rehabilitation Engineering	2024
Liu X.; Wu Y.; Li M	Identification of 7 mitochondria-related genes as diagnostic biomarkers of MDD and their correlation with immune infiltration: New insights from bioinformatics analysis	Journal of Affective Disorders	2024
Romero-Brufau S.; Macielak R.J.; Staab J.P.; Eggers S.D.Z.; Driscoll C.L.W.; Shepard N.T.; Totten D.J.; Albertson S.M.; Pasupathy K.S.; McCaslin D.L	Development of an Automated Triage System for Long-standing Dizzy Patients Using Artificial Intelligence	OTO Open	2024
Mese I.; Karaci R.; Taslicay C.A.; Taslicay C.; Akansel G.; Domac S.F	MRI radiomics based machine learning model of the periaqueductal gray matter in migraine patients	Ideggyogyaszati Szemle	2024
Jain A.; Raja R.; Srivastava S.; Sharma P.C.; Gangrade J.; R M	Analysis of EEG signals and data acquisition methods: a review	Computer Methods in Biomechanics and Biomedical Engineering: Imaging and Visualization	2024
Dahiya R.; Dahiya V.K.; Deepakshi; Agarwal N.; Maguluri L.P.; Muniyandy E	Predictive Modelling for Parkinson's Disease Diagnosis using Biomedical Voice Measurements	EAI Endorsed Transactions on Pervasive Health and Technology	2024
Eguchi K.; Yaguchi H.; Uwatoko H.; Iida Y.; Hamada S.; Honma S.; Takei A.; Moriwaka F.; Yabe I	Feasibility of differentiating gait in Parkinson's disease and spinocerebellar degeneration using a pose estimation algorithm in two-dimensional video	Journal of the Neurological Sciences	2024
Ji Y.; Silva R.F.; Adali T.; Wen X.; Zhu Q.; Jiang R.; Zhang D.; Qi S.; Calhoun V.D	Joint multi-site domain adaptation and multi-modality feature selection for the diagnosis of psychiatric disorders	NeuroImage: Clinical	2024
Xia Z.; Zhou T.; Jiao Z.; Lu J	Learnable Brain Connectivity Structures for Identifying Neurological Disorders	IEEE Transactions on Neural Systems and Rehabilitation Engineering	2024
Sakharova T.; Mao S.; Osadchuk M	Updated Models of Alzheimer's Disease with Deep Neural Networks	Journal of Alzheimer's Disease	2024
Ohi K.; Tanaka Y.; Otowa T.; Shimada M.; Kaiya H.; Nishimura F.; Sasaki T.; Tanii H.; Shioiri T.; Hara T	Discrimination between healthy participants and people with panic disorder based on polygenic scores for psychiatric disorders and for intermediate phenotypes using machine learning	Australian and New Zealand Journal of Psychiatry	2024

Table 1 (continued)

Authors	Title	Journal	Year
Adhikary S.; Varalasetty S.D.; Nadella S.T.; Ghosh A.; Nandi S	PrivLet: A differential privacy and inverse wavelet decomposition framework for secure and optimized hemiplegic gait classification	Biomedical Signal Processing and Control	2024
Salami A.; Andreu-Perez J.; Gillmeister H	Finding neural correlates of depersonalisation/derealisation disorder via explainable CNN-based analysis guided by clinical assessment scores	Artificial Intelligence in Medicine	2024
Zou Q.; Shang J.; Liu J.; Gao R	BIGFormer: A Graph Transformer with Local Structure Awareness for Diagnosis and Pathogenesis Identification of Alzheimer&# × 0027;s Disease Using Imaging Genetic Data	IEEE Journal of Biomedical and Health Informatics	2024
Sukhadia N.; Kamboj P	IMU-Based Approach to Detect Spastic Cerebral Palsy in Infants at Early Stages	EAI Endorsed Transactions on Pervasive Health and Technology	2024
Rifino N.; Bersano A.; Padovani A.; Conti G.M.; Cavallini A.; Colombo L.; Priori A.; Pianese R.; Gammone M.R.; Erbetta A.; Ciceri E.F.; Sattin D.; Varvello R.; Parati E.A.; Scelzo E.; Antozzi C.; Pareyson D.; Silvani A.; Finocchiaro G.; Farago' G.; Fariselli L.; Bruzzone M.G.; Carriero M.; Leonardi M.; Mantegazza R.; Eleopra R.; DiMeco F.; Ferroli P.; Pollo B.; Mariotti C.; Casali C.; Pantaleoni C.; Ciano C.; Cazzato D.; Anghileri E.; Doniselli F.; Acerbi F.; Giaccone G.; Zorzi G.; Vetrano I.G.; Moroni I.; Brambilla L.; Maggi L.; Nanetti L.; Romito L.M.; Chiapparini L.; Marchetti M.; Moscatelli M.E.M.; Schiariti M.P.; Grisoli M.; Broggi M.A.; Nardocci N.; Lanteri P.; Confalonieri P.A.; Tiraboschi P.; Morlino S.; Esposito S.; D'Arrigo S.; Clerici V.T.; Cuccarini V.; Zibordi F.; Saletti V.; Lucchini V.; Magno S.; Persico A.; Tosi P.; Boadu W.; Nava S.; Gipponi S.; Volonghi I.; Pezzini A.; Poli L.; Caratozzolo S.; Cristillo V.; Ranelli R.; Cosseddu M.; Turrone R.; Benazzo M.; Del Maestro M.; Luzzi S.; Zoia C.; Sacco S.; Ornello R.; Mariangela V	Virtual hospital and artificial intelligence: a first step towards the application of an innovative health system for the care of rare cerebrovascular diseases	Neurological Sciences	2024
Yu H.; Fan L.; Li L.; Zhou J.; Ma Z.; Xian L.; Hua W.; He S.; Jin M.; Zhang Y.; Gandhi A.; Ma X	Large Language Models in Biomedical and Health Informatics: A Review with Bibliometric Analysis	Journal of Healthcare Informatics Research	2024
Xu X.; Zhu G.; Li B.; Lin P.; Li X.; Wang Z	Automated diagnosis of schizophrenia based on spatial–temporal residual graph convolutional network	BioMedical Engineering Online	2024
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Table 1 (continued)

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Xu W.; Rong Z.; Ma W.; Zhu B.; Li N.; Huang J.; Liu Z.; Yu Y.; Zhang F.; Zhang X.; Ge M.; Hou Y	Improving the classification of multiple sclerosis and cerebral small vessel disease with interpretable transfer attention neural network	Computers in Biology and Medicine	2024
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Lahnakoski J.M.; Nolte T.; Solway A.; Vilares I.; Hula A.; Feigenbaum J.; Lohrenz T.; King-Casas B.; Fonagy P.; Montague P.R.; Schilbach L	A machine-learning approach for differentiating borderline personality disorder from community participants with brain-wide functional connectivity	Journal of Affective Disorders	2024
Mao L.; Hong X.; Hu M	Identifying neuroimaging biomarkers in major depressive disorder using machine learning algorithms and functional near-infrared spectroscopy (fNIRS) during verbal fluency task	Journal of Affective Disorders	2024
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Zhao P.; Alencastre-Miranda M.; Shen Z.; O'Neill C.; Whiteman D.; Gervas-Arruga J.; Igo Krebs H	Computer Vision for Gait Assessment in Cerebral Palsy: Metric Learning and Confidence Estimation	IEEE Transactions on Neural Systems and Rehabilitation Engineering	2024
Skaramagkas V.; Pentari A.; Kefalopoulou Z.; Tsiknakis M	Multi-Modal Deep Learning Diagnosis of Parkinson's Disease—A Systematic Review	IEEE Transactions on Neural Systems and Rehabilitation Engineering	2023
McCradden M.; Hui K.; Buchman D.Z	Evidence, ethics and the promise of artificial intelligence in psychiatry	Journal of Medical Ethics	2023
Sathyanarayanan A.; Mueller T.T.; Ali Moni M.; Schueler K.; Baune B.T.; Lio P.; Mehta D.; Baune B.T.; Dierssen M.; Ebert B.; Fabbri C.; Fusar-Poli P.; Gennarelli M.; Harmer C.; Howes O.D.; Janzing J.G.E.; Maron E.; Minelli A.; Nonell L.; Pisanu C.; Potier M.-C.; Rybakowski F.; Serretti A.; Sqassina A.; Stacey D.; van Westrhenen R.; Xicota L	Multi-omics data integration methods and their applications in psychiatric disorders	European Neuropsychopharmacology	2023
Campos-Ugaz W.A.; Palacios Garay J.P.; Rivera-Lozada O.; Alarcón Diaz M.A.; Fuster-Guillén D.; Tejada Arana A.A	An Overview of Bipolar Disorder Diagnosis Using Machine Learning Approaches: Clinical Opportunities and Challenges	Iranian Journal of Psychiatry	2023

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Gende M.; Mallen V.; De Moura J.; Cordon B.; Garcia-Martin E.; Sanchez C.I.; Novo J.; Ortega M	Automatic Segmentation of Retinal Layers in Multiple Neurodegenerative Disorder Scenarios	IEEE Journal of Biomedical and Health Informatics	2023
Beaulieu-Jones B.K.; Villamar M.F.; Scordis P.; Bartmann A.P.; Ali W.; Wissel B.D.; Alsentzer E.; de Jong J.; Patra A.; Kohane I	Predicting seizure recurrence after an initial seizure-like episode from routine clinical notes using large language models: a retrospective cohort study	The Lancet Digital Health	2023
Gifford A.; Praschan N.; Newhouse A.; Chemali Z	Biomarkers in frontotemporal dementia: Current landscape and future directions	Biomarkers in Neuropsychiatry	2023
Abbas S.Q.; Chi L.; Chen Y.-P.P	DeepMNF: Deep Multimodal Neuroimaging Framework for Diagnosing Autism Spectrum Disorder	Artificial Intelligence in Medicine	2023
Shah S.J.H.; Albishri A.; Kang S.S.; Lee Y.; Sponheim S.R.; Shim M	ETSNet: A deep neural network for EEG-based temporal–spatial pattern recognition in psychiatric disorder and emotional distress classification	Computers in Biology and Medicine	2023
Sugden R.J.; Diamandis P	Generalizable electroencephalographic classification of Parkinson's disease using deep learning	Informatics in Medicine Unlocked	2023
Hofman A.; Lier I.; Ikram M.A.; Van Wingerden M.; Luik A.I	Uncovering psychiatric phenotypes using unsupervised machine learning: A data-driven symptoms approach	European Psychiatry	2023
Wiem T.; Ali D	Deep second generation wavelet autoencoders based on curvelet pooling for brain pathology classification	Biomedical Signal Processing and Control	2023
Hata M.; Watanabe Y.; Tanaka T.; Awata K.; Miyazaki Y.; Fukuma R.; Taomoto D.; Satake Y.; Suehiro T.; Kanemoto H.; Yoshiyama K.; Iwase M.; Ikeda S.; Nishida K.; Takekita Y.; Yoshimura M.; Ishii R.; Kazui H.; Harada T.; Kishima H.; Ikeda M.; Yanagisawa T	Precise Discrimination for Multiple Etiologies of Dementia Cases Based on Deep Learning with Electroencephalography	Neuropsychobiology	2023
Su Q.; Bi F.; Yang S.; Yan H.; Sun X.; Wang J.; Qiu Y.; Li M.; Li S.; Li J	Identification of Plasma Biomarkers in Drug-Naïve Schizophrenia Using Targeted Metabolomics	Psychiatry Investigation	2023
Enrico P.; Delvecchio G.; Turtulici N.; Aronica R.; Pigoni A.; Squarcina L.; Villa F.M.; Perlini C.; Rossetti M.G.; Bellani M.; Lasalvia A.; Bonetto C.; Scocco P.; D'Agostino A.; Torresani S.; Imbesi M.; Bellini F.; Veronese A.; Bocchio-Chiavetto L.; Gennarelli M.; Balestrieri M.; Colombo G.I.; Finardi A.; Ruggeri M.; Furlan R.; Brambilla P.; Bertani M.E.; Bissoli S.; Cristofalo D.; De Santi K.; Lunardi S.; Negretto V.; Poli S.; Tosato S.; Zamboni M.G.; Ballarin M.; De Girolamo G.; Fioritti A.; Neri G.; Pileggi F.; Rucci P.; Chiavetto L.B.; Scasselatti C.; Zanardini R.; Bertoldo A.; Marinelli V.; Rambaldelli G	A machine learning approach on whole blood immunomarkers to identify an inflammation-associated psychosis onset subgroup	Molecular Psychiatry	2023
Xiao F.; Caciagli L.; Wandschneider B.; Sone D.; Young A.L.; Vos S.B.; Winston G.P.; Zhang Y.; Liu W.; An D.; Kanber B.; Zhou D.; Sander J.W.; Thom M.; Duncan J.S.; Alexander D.C.; Galovic M.; Koepp M.J	Identification of different MRI atrophy progression trajectories in epilepsy by subtype and stage inference	Brain	2023
Cui J.; Miao X.; Yanghao X.; Qin X	Bibliometric research on the developments of artificial intelligence in radiomics toward nervous system diseases	Frontiers in Neurology	2023

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Orrù G.; De Marchi B.; Sartori G.; Gemignani A.; Scarpazza C.; Monaro M.; Mazza C.; Roma P	Machine learning item selection for short scale construction: A proof-of-concept using the SIMS	Clinical Neuropsychologist	2023
Chen S.; Duan J.; Zhang N.; Qi M.; Li J.; Wang H.; Wang R.; Ju R.; Duan Y.; Qi S	MSA-YOLOv5: Multi-scale attention-based YOLOv5 for automatic detection of acute ischemic stroke from multi-modality MRI images	Computers in Biology and Medicine	2023
Du Z.; Peng R.; Liu W.; Li W.; Wu D	Mixture of Experts for EEG-Based Seizure Subtype Classification	IEEE Transactions on Neural Systems and Rehabilitation Engineering	2023
Purrer V.; Pohl E.; Lueckel J.M.; Borger V.; Sauer M.; Radbruch A.; Wüllner U.; Schmeel F.C	Artificial-intelligence-based MRI brain volumetry in patients with essential tremor and tremor-dominant Parkinson's disease	Brain Communications	2023
Chen Z.; Liu X.; Yang Q.; Wang Y.-J.; Miao K.; Gong Z.; Yu Y.; Leonov A.; Liu C.; Feng Z.; Chuan-Peng H	Evaluation of Risk of Bias in Neuroimaging-Based Artificial Intelligence Models for Psychiatric Diagnosis: A Systematic Review	JAMA Network Open	2023
Zaree M.; Mohebbi M.; Rostami R	An ensemble-based Machine learning technique for dyslexia detection during a visual continuous performance task	Biomedical Signal Processing and Control	2023
Aderinwale A.; Tolossa G.B.; Kim A.Y.; Jang E.H.; Lee Y.-I.; Jeon H.J.; Kim H.; Yu H.Y.; Jeong J	Two-channel EEG based diagnosis of panic disorder and major depressive disorder using machine learning and non-linear dynamical methods	Psychiatry Research—Neuroimaging	2023
Dergaa I.; Fekih-Romdhane F.; Hallit S.; Loch A.A.; Glenn J.M.; Fessi M.S.; Ben Aissa M.; Souissi N.; Guelmami N.; Swed S.; El Omri A.; Bragazzi N.L.; Ben Saad H	ChatGPT is not ready yet for use in providing mental health assessment and interventions	Frontiers in Psychiatry	2023
Ford J.D	Why We Need a Developmentally Appropriate Trauma Diagnosis for Children: a 10-Year Update on Developmental Trauma Disorder	Journal of Child and Adolescent Trauma	2023
Amsalam A.S.; Al-Naji A.; Daeef A.Y.; Chahl J	Automatic Facial Palsy, Age and Gender Detection Using a Raspberry Pi	BioMedInformatics	2023
Bartal A.; Jagodnik K.M.; Chan S.J.; Babu M.S.; Dekel S	Identifying women with postdelivery posttraumatic stress disorder using natural language processing of personal childbirth narratives	American Journal of Obstetrics and Gynecology MFM	2023
Kaplan E.; Chan W.Y.; Altinsoy H.B.; Baygin M.; Barua P.D.; Chakraborty S.; Dogan S.; Tuncer T.; Acharya U.R	PFP-HOG: Pyramid and Fixed-Size Patch-Based HOG Technique for Automated Brain Abnormality Classification with MRI	Journal of Digital Imaging	2023
Delgado-García G.; Engbers J.D.T.; Wiebe S.; Mouches P.; Amador K.; Forkert N.D.; White J.; Sajobi T.; Klein K.M.; Josephson C.B	Machine learning using multimodal clinical, electroencephalographic, and magnetic resonance imaging data can predict incident depression in adults with epilepsy: A pilot study	Epilepsia	2023
Sheng X.; Chen J.; Liu Y.; Hu B.; Cai H	Deep Manifold Harmonic Network With Dual Attention for Brain Disorder Classification	IEEE Journal of Biomedical and Health Informatics	2023

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Wu L.; Zhao Q.; Liu J.; Yu H	Efficient identification of Alzheimer's brain dynamics with Spatial–Temporal Autoencoder: A deep learning approach for diagnosing brain disorders	Biomedical Signal Processing and Control	2023
Liu Z.; Luo S.; Lu Y.; Zhang Y.; Jiang L.; Xiao H	Extracting Multi-Scale and Salient Features by MSE Based U-Structure and CBAM for Sleep Staging	IEEE Transactions on Neural Systems and Rehabilitation Engineering	2023
Almufareh M.F.; Tehsin S.; Humayun M.; Kausar S	Artificial Cognition for Detection of Mental Disability: A Vision Transformer Approach for Alzheimer's Disease	Healthcare (Switzerland)	2023
Shangguan Z.; Liu Z.; Li G.; Chen Q.; Ding Z.; Hu B	Dual-Stream Multiple Instance Learning for Depression Detection With Facial Expression Videos	IEEE Transactions on Neural Systems and Rehabilitation Engineering	2023
Oliveira-Saraiva D.; Ferreira H.A	Normative model detects abnormal functional connectivity in psychiatric disorders	Frontiers in Psychiatry	2023
Emre İ.E.; Erol Ç.; Taş C.; Tarhan N	Multi-class classification model for psychiatric disorder discrimination	International Journal of Medical Informatics	2023
Condino F.; Crocco M.C.; Pirritano D.; Petrone A.; Del Giudice F.; Guzzi R	A Linear Predictor Based on FTIR Spectral Biomarkers Improves Disease Diagnosis Classification: An Application to Multiple Sclerosis	Journal of Personalized Medicine	2023
Fanos V.; Dessì A.; Deledda L.; Lai A.; Ranzi P.; Avellino I.; Marinaro F.; Petza S.; Pintus R.; Oliverio G.; Vitale S.G.; Angioni S.; Colangelo A	Postpartum depression screening through artificial intelligence: preliminary data through the Talking About algorithm	Journal of Pediatric and Neonatal Individualized Medicine	2023
Recenti M.; Gargiulo P.; Chang M.; Ko S.B.; Kim T.J.; Ko S.U	Predicting stroke, neurological and movement disorders using single and dual-task gait in Korean older population	Gait and Posture	2023
Gengeç Benli Ş	Classification of First-Episode Psychosis with EEG Signals: ciSSA and Machine Learning Approach	Biomedicines	2023
Oh J.; Lee T.; Chung E.S.; Kim H.; Cho K.; Kim H.; Choi J.; Sim H.-H.; Lee J.; Choi I.Y.; Kim D.-J	Development of depression detection algorithm using text scripts of routine psychiatric interview	Frontiers in Psychiatry	2023
Vukojević J.; Mulc D.; Kinder I.; Jovičić E.; Friganović K.; Savić A.; Cifrek M.; Vidović D	Borderline and Depression: A Thin EEG Line	Clinical EEG and Neuroscience	2023
Dembovskiy M.V.; Boiko A.A	Automated assessment of facial nerve dysfunction	Digital Diagnostics	2023
Franken K.; ten Klooster P.; Bohlmeijer E.; Westerhof G.; Kraiss J	Predicting non-improvement of symptoms in daily mental healthcare practice using routinely collected patient-level data: a machine learning approach	Frontiers in Psychiatry	2023
Li Q.; Wang W.; Hu Z	Amygdala's T1-weighted image radiomics outperforms volume for differentiation of anxiety disorder and its subtype	Frontiers in Psychiatry	2023
Ajra Z.; Xu B.; Dray G.; Montmain J.; Perrey S	Using shallow neural networks with functional connectivity from EEG signals for early diagnosis of Alzheimer's and frontotemporal dementia	Frontiers in Neurology	2023

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Chun-Hung L.; Guan-Hsiung L.; Wu-Chuan Y.; Yu-Hsin L	Analysis of EEG characteristics of schizophrenic patients by CNN-Attention algorithm	Revista de Psiquiatria Clinica	2023
Cansel N.; Alcin Ö.F.; Yılmaz Ö.F.; Ari A.; Akan M.; Ucuz İ	A NEW ARTIFICIAL INTELLIGENCE-BASED CLINICAL DECISION SUPPORT SYSTEM FOR DIAGNOSIS OF MAJOR PSYCHIATRIC DISEASES BASED ON VOICE ANALYSIS	Psychiatria Danubina	2023
Slaby I.; Hain H.S.; Abrams D.; Mentch F.D.; Glessner J.T.; Sleiman P.M.A.; Hakonarson H	An electronic health record (EHR) phenotype algorithm to identify patients with attention deficit hyperactivity disorders (ADHD) and psychiatric comorbidities	Journal of Neurodevelopmental Disorders	2022
Weber S.; Heim S.; Richiardi J.; Van De Ville D.; Serranová T.; Jech R.; Marapin R.S.; Tijssen M.A.J.; Aybek S	Multi-centre classification of functional neurological disorders based on resting-state functional connectivity	NeuroImage: Clinical	2022
Vera Cruz G.; Bucourt E.; Réveillère C.; Martaillé V.; Joncker-Vannier I.; Goupille P.; Mulleman D.; Courtois R	Machine learning reveals the most important psychological and social variables predicting the differential diagnosis of rheumatic and musculoskeletal diseases	Rheumatology International	2022
Hu M.; Qian X.; Liu S.; Koh A.J.; Sim K.; Jiang X.; Guan C.; Zhou J.H	Structural and diffusion MRI based schizophrenia classification using 2D pretrained and 3D naive Convolutional Neural Networks	Schizophrenia Research	2022
Kumar G.; Chander S.; Almadhor A	An intelligent epilepsy seizure detection system using adaptive mode decomposition of EEG signals	Physical and Engineering Sciences in Medicine	2022
Wen G.; Cao P.; Bao H.; Yang W.; Zheng T.; Zaiane O	MVS-GCN: A prior brain structure learning-guided multi-view graph convolution network for autism spectrum disorder diagnosis	Computers in Biology and Medicine	2022
Drobinin V.; Van Gestel H.; Helmick C.A.; Schmidt M.H.; Bowen C.V.; Uher R	The Developmental Brain Age Is Associated With Adversity, Depression, and Functional Outcomes Among Adolescents	Biological Psychiatry: Cognitive Neuroscience and Neuroimaging	2022
Bernardo L.S.; Damaševičius R.; Ling S.H.; de Albuquerque V.H.C.; Tavares J.M.R.S	Modified SqueezeNet Architecture for Parkinson's Disease Detection Based on Keypress Data	Biomedicines	2022
Kroemer N.B.; Opel N.; Teckentrup V.; Li M.; Grotegerd D.; Meinert S.; Lemke H.; Kircher T.; Nenadić I.; Krug A.; Jansen A.; Sommer J.; Steinsträter O.; Small D.M.; Dannlowski U.; Walter M	Functional Connectivity of the Nucleus Accumbens and Changes in Appetite in Patients with Depression	JAMA Psychiatry	2022
Shoeibi A.; Ghassemi N.; Khodatars M.; Moridian P.; Alizadehsani R.; Zare A.; Khosravi A.; Subasi A.; Rajendra Acharya U.; Gorriz J.M	Detection of epileptic seizures on EEG signals using ANFIS classifier, autoencoders and fuzzy entropies	Biomedical Signal Processing and Control	2022
Duan L.; Wang Z.; Qiao Y.; Wang Y.; Huang Z.; Zhang B	An Automatic Method for Epileptic Seizure Detection Based on Deep Metric Learning	IEEE Journal of Biomedical and Health Informatics	2022
Liu S.; Zhao L.; Zhao J.; Li B.; Wang S.-H	Attention deficit/hyperactivity disorder Classification based on deep spatio-temporal features of functional Magnetic Resonance Imaging	Biomedical Signal Processing and Control	2022

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Ma C.; Li D.; Pan L.; Li X.; Yin C.; Li A.; Zhang Z.; Zong R	Quantitative assessment of essential tremor based on machine learning methods using wearable device	Biomedical Signal Processing and Control	2022
Schwitzer T.; Leboyer M.; Laprévote V.; Louis Dorr V.; Schwan R	Using retinal electrophysiology toward precision psychiatry	European Psychiatry	2022
Mulders P.C.R.; van Eijndhoven P.F.P.; van Oort J.; Oldehinkel M.; Duyser F.A.; Kist J.D.; Collard R.M.; Vrijsen J.N.; Haak K.V.; Beckmann C.F.; Tendolkar I.; Marquand A.F	Striatal connectopic maps link to functional domains across psychiatric disorders	Translational Psychiatry	2022
Zhu M.; Men Q.; Ho E.S.L.; Leung H.; Shum H.P.H	A Two-stream Convolutional Network for Musculoskeletal and Neurological Disorders Prediction	Journal of Medical Systems	2022
Price G.D.; Heinz M.V.; Zhao D.; Nemesure M.; Ruan F.; Jacobson N.C	An unsupervised machine learning approach using passive movement data to understand depression and schizophrenia	Journal of Affective Disorders	2022
Caldirola D.; Daccò S.; Cuniberti F.; Grassi M.; Alciati A.; Torti T.; Perna G	First-onset major depression during the COVID-19 pandemic: A predictive machine learning model	Journal of Affective Disorders	2022
Li Z.; Li W.; Yan W.; Zhang R.; Xie S	Data-driven learning to identify biomarkers in bipolar disorder	Computer Methods and Programs in Biomedicine	2022
Xia C.H.; Barnett I.; Tapera T.M.; Adebimpe A.; Baker J.T.; Bassett D.S.; Brotman M.A.; Calkins M.E.; Cui Z.; Leibenluft E.; Linguiti S.; Lydon-Staley D.M.; Martin M.L.; Moore T.M.; Murtha K.; Piiwaa K.; Pines A.; Roalf D.R.; Rush-Goebel S.; Wolf D.H.; Ungar L.H.; Satterthwaite T.D	Mobile footprinting: linking individual distinctiveness in mobility patterns to mood, sleep, and brain functional connectivity	Neuropsychopharmacology	2022
Li D.; Qu J.; Tian Z.; Mou Z.; Zhang L.; Zhang X	Knowledge-Based Recurrent Neural Network for TCM Cerebral Palsy Diagnosis	Evidence-based Complementary and Alternative Medicine	2022
Caldirola D.; Cuniberti F.; Daccò S.; Grassi M.; Torti T.; Perna G	Predicting New-Onset Psychiatric Disorders Throughout the COVID-19 Pandemic: A Machine Learning Approach	Journal of Neuropsychiatry and Clinical Neurosciences	2022
König A.; Müller P.; Tröger J.; Lindsay H.; Alexandersson J.; Hinze J.; Riemenschneider M.; Postin D.; Ettore E.; Lecomte A.; Musiol M.; Amblard M.; Bremond F.; Balazia M.; Hurlemann R	Multimodal phenotyping of psychiatric disorders from social interaction: Protocol of a clinical multicenter prospective study	Personalized Medicine in Psychiatry	2022
Yu C.; Zhang F.-J.; Zhang L.-L.; Xian D.-X.; Li Y.; Li J.-J.; Tang S.-X.; Li X.-J.; Liu Y.; Peng M.; Zhang L.; Wang S	An approach combining bioinformatics and machine learning to identify eight autophagy-related biomarkers and construct molecular mechanisms underlying COVID-19 and major depressive disorders	European Review for Medical and Pharmacological Sciences	2022
Gradus J.L.; Rosellini A.J.; Szentkúti P.; Horváth-Puhó E.; Smith M.L.; Galatzer-Levy I.; Lash T.L.; Galea S.; Schnurr P.P.; Sørensen H.T	Pre-trauma predictors of severe psychiatric comorbidity 5 years following traumatic experiences	International Journal of Epidemiology	2022
Moro M.; Pastore V.P.; Tacchino C.; Durand P.; Blanchi I.; Moretti P.; Odone F.; Casadio M	A markerless pipeline to analyze spontaneous movements of preterm infants	Computer Methods and Programs in Biomedicine	2022
Ghosh C.C.; McVicar D.; Davidson G.; Shannon C.; Armour C	What can we learn about the psychiatric diagnostic categories by analysing patients' lived experiences with Machine-Learning?	BMC Psychiatry	2022

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Yao S.; Zhu J.; Li S.; Zhang R.; Zhao J.; Yang X.; Wang Y	Bibliometric Analysis of Quantitative Electroencephalogram Research in Neuropsychiatric Disorders From 2000 to 2021	Frontiers in Psychiatry	2022
Xu S.; Yang Z.; Chakraborty D.; Chua Y.H.V.; Tolomeo S.; Winkler S.; Birnbaum M.; Tan B.-L.; Lee J.; Dauwels J	Identifying psychiatric manifestations in schizophrenia and depression from audio-visual behavioural indicators through a machine-learning approach	Schizophrenia	2022
Li G.; Li T.; Li F.; Zhang C	NerveStitcher: Corneal confocal microscope images stitching with neural networks	Computers in Biology and Medicine	2022
Papst L.; Köllner V	Using machine learning to investigate earning capacity in patients undergoing psychosomatic rehabilitation—A retrospective health data analysis	Frontiers in Psychiatry	2022
AlGhamdi A.S	Novel Ensemble Model Recommendation Approach for the Detection of Dyslexia	Children	2022
Sipari D.; Chaparro-Rico B.D.M.; Cafolla D	SANE (Easy Gait Analysis System): Towards an AI-Assisted Automatic Gait-Analysis	International Journal of Environmental Research and Public Health	2022
Cotes R.O.; Boazak M.; Griner E.; Jiang Z.; Kim B.; Bremer W.; Seyedi S.; Rad A.B.; Clifford G.D	Multimodal Assessment of Schizophrenia and Depression Utilizing Video, Acoustic, Locomotor, Electroencephalographic, and Heart Rate Technology: Protocol for an Observational Study	JMIR Research Protocols	2022
Schulte E.C.; Kondofersky I.; Budde M.; Papiol S.; Senner F.; Schaupp S.K.; Reich-Erkelenz D.; Klöhn-Saghatolislam F.; Kalman J.L.; Gade K.; Hake M.; Comes A.L.; Anderson-Schmidt H.; Adorjan K.; Juckel G.; Schmauß M.; Zimmermann J.; Reimer J.; Wiltfang J.; Reininghaus E.Z.; Anghelescu I.-G.; Konrad C.; Figge C.; von Hagen M.; Jäger M.; Dietrich D.E.; Spitzer C.; Witt S.H.; Forstner A.J.; Rietschel M.; Nöthen M.M.; Falkai P.; Heilbronner U.; Mueller N.S.; Schulze T.G	A novel longitudinal clustering approach to psychopathology across diagnostic entities in the hospital-based PsyCourse study	Schizophrenia Research	2022
Kress G.T.; Chan F.; Garcia C.A.; Merrifield W.S	Utilizing machine learning algorithms to predict subject genetic mutation class from in silico models of neuronal networks	BMC Medical Informatics and Decision Making	2022
Azuma H.; Akechi T	EEG correlates of quality of life and associations with seizure without awareness and depression in patients with epilepsy	Neuropsychopharmacology Reports	2022
Heyrani R.; Sarabi-Jamab A.; Grafman J.; Asadi N.; Soltani S.; Mirfazeli F.S.; Almasi-Dooghaei M.; Shariat S.V.; Jahanbakhshi A.; Khoeini T.; Joghataei M.T	Limits on using the clock drawing test as a measure to evaluate patients with neurological disorders	BMC Neurology	2022
Schweitzer M.G	Introduction to President's Day. The Future: Promises and uncertainties of the future; [Introduction à la Journée du Président. Le Futur: promesses et incertitudes du devenir]	Annales Medico-Psychologiques	2022

Table 1 (continued)

Authors	Title	Journal	Year
Dilernia A.; Quevedo K.; Camchong J.; Lim K.; Pan W.; Zhang L	Penalized model-based clustering of fMRI data	Biostatistics	2022
Kim A.; Hsu M.; Koire A.; Baum M.L	Incidental Findings from Deep Phenotyping Research in Psychiatry: Legal and Ethical Considerations	Cambridge Quarterly of Healthcare Ethics	2022
Niu X.; Gou J.; Chang H.; Lowe M.; Zhang F	Classification model with weighted regularization to improve the reproducibility of neuroimaging signature selection	Statistics in Medicine	2022
Bessadok A.; Mahjoub M.A.; Rekik I	Brain graph synthesis by dual adversarial domain alignment and target graph prediction from a source graph	Medical Image Analysis	2021
Jiang T.; Nagy D.; Rosellini A.J.; Horváth-Puhó E.; Keyes K.M.; Lash T.L.; Galea S.; Sørensen H.T.; Gradus J.L	Suicide prediction among men and women with depression: A population-based study	Journal of Psychiatric Research	2021
Na K.-S.; Cho S.-E.; Cho S.-J	Machine learning-based discrimination of panic disorder from other anxiety disorders	Journal of Affective Disorders	2021
Pelin H.; Ising M.; Stein F.; Meinert S.; Meller T.; Brosch K.; Winter N.R.; Krug A.; Leenings R.; Lemke H.; Nenadić I.; Heilmann-Heimbach S.; Forstner A.J.; Nöthen M.M.; Opel N.; Repple J.; Pfarr J.; Ringwald K.; Schmitt S.; Thiel K.; Waltemate L.; Winter A.; Streit F.; Witt S.; Rietschel M.; Dannlowski U.; Kircher T.; Hahn T.; Müller-Myhsok B.; Andlauer T.F.M	Identification of transdiagnostic psychiatric disorder subtypes using unsupervised learning	Neuropsychopharmacology	2021
Marsch L.A	Digital health data-driven approaches to understand human behavior	Neuropsychopharmacology	2021
Uyulan C.; Ergüzel T.T.; Unubol H.; Cebi M.; Sayar G.H.; Nezhad Asad M.; Tarhan N	Major Depressive Disorder Classification Based on Different Convolutional Neural Network Models: Deep Learning Approach	Clinical EEG and Neuroscience	2021
Keding T.J.; Heyn S.A.; Russell J.D.; Zhu X.; Cisler J.; McLaughlin K.A.; Herringa R.J	Differential Patterns of Delayed Emotion Circuit Maturation in Abused Girls With and Without Internalizing Psychopathology	American Journal of Psychiatry	2021
Haynos A.F.; Wang S.B.; Lipson S.; Peterson C.B.; Mitchell J.E.; Halmi K.A.; Agras W.S.; Crow S.J	Machine learning enhances prediction of illness course: A longitudinal study in eating disorders	Psychological Medicine	2021
Zhan Y.; Wei J.; Liang J.; Xu X.; He R.; Robbins T.W.; Wang Z	Diagnostic classification for human autism and obsessive–compulsive disorder based on machine learning from a primate genetic model	American Journal of Psychiatry	2021
Sicorello M.; Thome J.; Herzog J.; Schmahl C	Differential Effects of Early Adversity and Posttraumatic Stress Disorder on Amygdala Reactivity: The Role of Developmental Timing	Biological Psychiatry: Cognitive Neuroscience and Neuroimaging	2021
Zhang Y.; Wu W.; Toll R.T.; Naparstek S.; Maron-Katz A.; Watts M.; Gordon J.; Jeong J.; Astolfi L.; Shpigel E.; Longwell P.; Sarhadi K.; El-Said D.; Li Y.; Cooper C.; Chin-Fatt C.; Arns M.; Goodkind M.S.; Trivedi M.H.; Marmar C.R.; Etkin A	Identification of psychiatric disorder subtypes from functional connectivity patterns in resting-state electroencephalography	Nature Biomedical Engineering	2021

Table 1 (continued)

Authors	Title	Journal	Year
Chang M.; Womer F.Y.; Gong X.; Chen X.; Tang L.; Feng R.; Dong S.; Duan J.; Chen Y.; Zhang R.; Wang Y.; Ren S.; Wang Y.; Kang J.; Yin Z.; Wei Y.; Wei S.; Jiang X.; Xu K.; Cao B.; Zhang Y.; Zhang W.; Tang Y.; Zhang X.; Wang F	Identifying and validating subtypes within major psychiatric disorders based on frontal–posterior functional imbalance via deep learning	Molecular Psychiatry	2021
Watts D.; Moulden H.; Mamak M.; Upfold C.; Chaimowitz G.; Kapczinski F	Predicting offenses among individuals with psychiatric disorders—A machine learning approach	Journal of Psychiatric Research	2021
Adams R.S.; Jiang T.; Rosellini A.J.; Horváth-Puhó E.; Street A.E.; Keyes K.M.; Cerdá M.; Lash T.L.; Sørensen H.T.; Gradus J.L	Sex-Specific Risk Profiles for Suicide Among Persons with Substance Use Disorders in Denmark	Addiction	2021
Pisani A.I.; Scalfari A.; Crescenzo F.; Romualdi C.; Calabrese M	A novel prognostic score to assess the risk of progression in relapsing – remitting multiple sclerosis patients	European Journal of Neurology	2021
Prasanna J.; Subathra M.S.P.; Mohammed M.A.; Damaševičius R.; Sairamya N.J.; George S.T	Automated epileptic seizure detection in pediatric subjects of chb-mit eeg database—a survey	Journal of Personalized Medicine	2021

Table 1 (continued)

Authors	Title	Journal	Year
Estiri H.; Strasser Z.H.; Brat G.A.; Semenov Y.R.; Aaron J.R.; Agapito G.; Albayrak A.; Alessiani M.; Amendola D.F.; Anthony L.L.L.J.; Aronow B.J.; Ashraf F.; Atz A.; Avillach P.; Balshi J.; Beaulieu-Jones B.K.; Bell D.S.; Bellasi A.; Bellazzi R.; Benoit V.; Beraghi M.; Sobrino J.L.B.; Bernaux M.; Bey R.; Martínez A.B.; Boeker M.; Bonzel C.-L.; Booth J.; Bosari S.; Bourgeois F.T.; Bradford R.L.; Bréant S.; Brown N.W.; Bryant W.A.; Bucalo M.; Burgun A.; Cai T.; Cannataro M.; Carmona A.; Caucheteux C.; Champ J.; Chen J.; Chen K.; Chiovato L.; Chiudinelli L.; Cho K.; Cimino J.J.; Colicchio T.K.; Cormont S.; Cossin S.; Craig J.B.; Bermúdez J.L.C.; Rojo J.C.; Dagliati A.; Daniar M.; Daniel C.; Davoudi A.; Devkota B.; Dubiel J.; Esteve L.; Fan S.; Follett R.W.; Gaiolla P.S.A.; Ganslandt T.; Barrio N.G.; Garmire L.X.; Gehlenborg N.; Geva A.; Gradinger T.; Gramfort A.; Griffier R.; Griffon N.; Grisel O.; Gutiérrez-Sacristán A.; Hanauer D.A.; Haverkamp C.; He B.; Henderson D.W.; Hilka M.; Holmes J.H.; Hong C.; Horki P.; Huling K.M.; Hutch M.R.; Issitt R.W.; Jannot A.S.; Jouhet V.; Keller M.S.; Kirchoff K.; Klann J.G.; Kohane I.S.; Krantz I.D.; Kraska D.; Krishnamurthy A.K.; L'Yi S.; Le T.T.; Leblanc J.; Leite A.R.R.; Lemaitre G.; Lenert L.; Leprovost D.; Liu M.; Loh N.H.W.; Lozano-Zahonero S.; Luo Y.; Lynch K.E.; Mahmood S.; Maidlow S.; Malovini A.; Mandl K.D.; Mao C.; Maram A.; Martel P.; Masino A.J.; Mazzitelli M.; Mensch A.; Milano M.; Minicucci M.F.; Moal B.; Moore J.H.; Moraleda C.; Morris J.S.; Morris M.; Moshal K.L.; Mousavi S.; Mowery D.L.; Murad D.A.; Naughton T.P.; Neuraz A.; Ngiam K.Y.; Norman J.B.; Obeid J.; Okoshi M.P.; Olson K.L.; Omenn G.S.; Orlova N.; Ostasiewski B.D.; Palmer N.P.; Paris N.; Patel L.P.; Jimenez M.P.; Pfaff E.R.; Pillion D.; Prokosch H.U.; Prudente R.A.; González V.Q.; Ramoni R.B.; Raskin M.; Rieg S.; Domínguez G.R.; Rojo P.; Sáez C.; Salamanca E.; Samayamuthu M.J.; Sandrin A.; Santos J.C.C.; Savino M.; Schriver E.R.; Schubert P.; Schuettler J.; Scudeller L.; Sebire N.J.; Balazote P.S.; Serre P.; Serret-Larmande A.; Shakeri Z.; Silvio D.; Sliz P.; Son J.; Sonday C.; South A.M.; Spiridou A.; Tan A.L.M.; Tan B.W.Q.; Tan B.W.L.; Tanni S.E.; Taylor D.M.; Terriza Torres A.I.; Tibollo V.; Tippmann P.; Torti C.; Trecarichi E.M.; Tseng Y.-J.; Vallejos A.K.; Varoquaux G.; Vella M.E.; Verdy G.; Vie J.-J.; Visweswaran S.; Vitacca M.; Wagholikar K.B.; Waitman L.R.; Wang X.; Wassermann D.; Weber G.M.; Xia Z.; Yehya N.; Yuan W.; Zambelli A.; Zhang H.G.; Zoeller D.; Zucco C.; Murphy S.N.; Patel C.J	Evolving phenotypes of non-hospitalized patients that indicate long COVID	BMC Medicine	2021
Komatsu H.; Watanabe E.; Fukuchi M	Psychiatric neural networks and precision therapeutics by machine learning	Biomedicines	2021

Table 1 (continued)

Authors	Title	Journal	Year
Zhang Q.; Liao Y.; Wang X.; Zhang T.; Feng J.; Deng J.; Shi K.; Chen L.; Feng L.; Ma M.; Xue L.; Hou H.; Dou X.; Yu C.; Ren L.; Ding Y.; Chen Y.; Wu S.; Chen Z.; Zhang H.; Zhuo C.; Tian M	A deep learning framework for 18F-FDG PET imaging diagnosis in pediatric patients with temporal lobe epilepsy	European Journal of Nuclear Medicine and Molecular Imaging	2021
Gokten E.S.; Uyulan C	Prediction of the development of depression and post-traumatic stress disorder in sexually abused children using a random forest classifier	Journal of Affective Disorders	2021
Movaghar A.; Page D.; Scholze D.; Hong J.; DaWalt L.S.; Kuusisto F.; Stewart R.; Brilliant M.; Mailick M	Artificial intelligence–assisted phenotype discovery of fragile X syndrome in a population-based sample	Genetics in Medicine	2021
Yamashita A.; Sakai Y.; Yamada T.; Yahata N.; Kunimatsu A.; Okada N.; Itahashi T.; Hashimoto R.; Mizuta H.; Ichikawa N.; Takamura M.; Okada G.; Yamagata H.; Harada K.; Matsuo K.; Tanaka S.C.; Kawato M.; Kasai K.; Kato N.; Takahashi H.; Okamoto Y.; Yamashita O.; Imamizu H	Common Brain Networks Between Major Depressive-Disorder Diagnosis and Symptoms of Depression That Are Validated for Independent Cohorts	Frontiers in Psychiatry	2021
Zhou Z.; Wang K.; Tang J.; Wei D.; Song L.; Peng Y.; Fu Y.; Qiu J	Cortical thickness distinguishes between major depression and schizophrenia in adolescents	BMC Psychiatry	2021
Stassen H.H.; Bachmann S.; Bridler R.; Cattapan K.; Herzig D.; Schneeberger A.; Seifritz E	Inflammatory processes linked to major depression and schizophrenic disorders and the effects of polypharmacy in psychiatry: evidence from a longitudinal study of 279 patients under therapy	European Archives of Psychiatry and Clinical Neuroscience	2021
Huang M.-X.; Huang C.W.; Harrington D.L.; Robb-Swan A.; Angeles-Quinto A.; Nichols S.; Huang J.W.; Le L.; Rimmele C.; Matthews S.; Drake A.; Song T.; Ji Z.; Cheng C.-K.; Shen Q.; Foote E.; Lerman I.; Yurgil K.A.; Hansen H.B.; Naviaux R.K.; Dynes R.; Baker D.G.; Lee R.R	Resting-state magnetoencephalography source magnitude imaging with deep-learning neural network for classification of symptomatic combat-related mild traumatic brain injury	Human Brain Mapping	2021
Lenio S.; Kerr W.T.; Watson M.; Baker S.; Bush C.; Rajic A.; Strom L	Validation of a predictive calculator to distinguish between patients presenting with dissociative versus epileptic seizures	Epilepsy and Behavior	2021
Shen H.; Wang S.-H.; Zhang Y.; Wang H.; Li F.; Lucas M.V.; Zhang Y.-D.; Liu Y.; Yuan T.-F	Color painting predicts clinical symptoms in chronic schizophrenia patients via deep learning	BMC Psychiatry	2021
Culbreth A.J.; Waltz J.A.; Frank M.J.; Gold J.M	Retention of Value Representations Across Time in People With Schizophrenia and Healthy Control Subjects	Biological Psychiatry: Cognitive Neuroscience and Neuroimaging	2021
Kaczmarek A.T.; Bahlmann N.; Thaqi B.; May P.; Schwarz G	Machine learning-based identification and characterization of 15 novel pathogenic SUOX missense mutations	Molecular Genetics and Metabolism	2021
Alarcón-Narváez D.; Hernández-Torruco J.; Hernández-Ocaña B.; Chávez-Bosquez O.; Marchi J.; Méndez-Castillo J.J	Toward a machine learning model for a primary diagnosis of Guillain-Barré syndrome subtypes	Health Informatics Journal	2021
Videtič Paska A.; Kouter K	Machine learning as the new approach to understand biomarkers of suicidal behavior	Bosnian Journal of Basic Medical Sciences	2021
McGinnis E.W.; Scism J.; Hruschak J.; Muzik M.; Rosenblum K.L.; Fitzgerald K.; Copeland W.; McGinnis R.S	Digital Phenotype for Childhood Internalizing Disorders: Less Positive Play and Promise for a Brief Assessment Battery	IEEE Journal of Biomedical and Health Informatics	2021

Table 1 (continued)

Authors	Title	Journal	Year
Hasan S.; Kulkarni A.K.; Parija S.; Dash P.K	A systematic review on detection and estimation algorithms of EEG signal for epilepsy	International Journal of Medical Engineering and Informatics	2021
Steardo L., Jr.; Carbone E.A.; Filippis R.; Pisanu C.; Segura-Garcia C.; Squassina A.; De Fazio P.; Steardo L	Application of support vector machine on fmri data as biomarkers in schizophrenia diagnosis: A systematic review	Frontiers in Psychiatry	2020
Chang Y.-W.; Tsai S.-J.; Wu Y.-F.; Yang A.C	Development of an AI-Based Web Diagnostic System for Phenotyping Psychiatric Disorders	Frontiers in Psychiatry	2020
Koesmahargyo V.; Abbas A.; Zhang L.; Guan L.; Feng S.; Yadav V.; Galatzer-Levy I.R	Accuracy of machine learning-based prediction of medication adherence in clinical research	Psychiatry Research	2020
Rebsamen M.; Suter Y.; Wiest R.; Reyes M.; Rummel C	Brain Morphometry Estimation: From Hours to Seconds Using Deep Learning	Frontiers in Neurology	2020
Gautam R.; Sharma M	Prevalence and Diagnosis of Neurological Disorders Using Different Deep Learning Techniques: A Meta-Analysis	Journal of Medical Systems	2020
Thoduparambil P.P.; Dominic A.; Varghese S.M	EEG-based deep learning model for the automatic detection of clinical depression	Physical and Engineering Sciences in Medicine	2020
Calhas D.; Romero E.; Henriques R	On the use of pairwise distance learning for brain signal classification with limited observations	Artificial Intelligence in Medicine	2020
Mellem M.S.; Liu Y.; Gonzalez H.; Kollada M.; Martin W.J.; Ahammad P	Machine Learning Models Identify Multimodal Measurements Highly Predictive of Transdiagnostic Symptom Severity for Mood, Anhedonia, and Anxiety	Biological Psychiatry: Cognitive Neuroscience and Neuroimaging	2020
Amin H.U.; Yusoff M.Z.; Ahmad R.F	A novel approach based on wavelet analysis and arithmetic coding for automated detection and diagnosis of epileptic seizure in EEG signals using machine learning techniques	Biomedical Signal Processing and Control	2020
Chen L.; Xia C.; Sun H	Recent advances of deep learning in psychiatric disorders	Precision Clinical Medicine	2020
Islam M.S.; El-Hajj A.M.; Alawieh H.; Dawy Z.; Abbas N.; El-Imad J	EEG mobility artifact removal for ambulatory epileptic seizure prediction applications	Biomedical Signal Processing and Control	2020
Gradus J.L.; Rosellini A.J.; Horváth-Puhó E.; Street A.E.; Galatzer-Levy I.; Jiang T.; Lash T.L.; Sørensen H.T	Prediction of Sex-Specific Suicide Risk Using Machine Learning and Single-Payer Health Care Registry Data from Denmark	JAMA Psychiatry	2020
Morris L.S.; Tan A.; Smith D.A.; Grehl M.; Han-Huang K.; Naidich T.P.; Charney D.S.; Balchandani P.; Murrough J.W.; Kundu P	Sub-millimeter variation in human locus coeruleus is associated with dimensional measures of psychopathology: An in vivo ultra-high field 7-Tesla MRI study	NeuroImage: Clinical	2020
Zhang J.; Li X.; Li Y.; Wang M.; Huang B.; Yao S.; Shen L	Three dimensional convolutional neural network-based classification of conduct disorder with structural MRI	Brain Imaging and Behavior	2020
Caye A.; Agnew-Blais J.; Arseneault L.; Gonçalves H.; Kieling C.; Langley K.; Menezes A.M.B.; Moffitt T.E.; Passos I.C.; Rocha T.B.; Sibley M.H.; Swanson J.M.; Thapar A.; Wehrmeister F.; Rohde L.A	A risk calculator to predict adult attention-deficit/hyperactivity disorder: generation and external validation in three birth cohorts and one clinical sample	Epidemiology and Psychiatric Sciences	2020
Mhiri I.; Khalifa A.B.; Mahjoub M.A.; Rekik I	Brain graph super-resolution for boosting neurological disorder diagnosis using unsupervised multi-topology connectional brain template learning	Medical Image Analysis	2020

Table 1 (continued)

Authors	Title	Journal	Year
Worthington M.A.; Mandavia A.; Richardson-Vejlgaard R	Prospective prediction of PTSD diagnosis in a nationally representative sample using machine learning	BMC Psychiatry	2020
Zhang X.; Yao L.; Dong M.; Liu Z.; Zhang Y.; Li Y	Adversarial Representation Learning for Robust Patient-Independent Epileptic Seizure Detection	IEEE Journal of Biomedical and Health Informatics	2020
Chen J.; Zang Z.; Braun U.; Schwarz K.; Harneit A.; Kremer T.; Ma R.; Schweiger J.; Moessnang C.; Geiger L.; Cao H.; Degenhardt F.; Nöthen M.M.; Tost H.; Meyer-Lindenberg A.; Schwarz E	Association of a Reproducible Epigenetic Risk Profile for Schizophrenia with Brain Methylation and Function	JAMA Psychiatry	2020
Nicholson A.A.; Harricharan S.; Densmore M.; Neufeld R.W.J.; Ros T.; McKinnon M.C.; Frewen P.A.; Théberge J.; Jetly R.; Pedlar D.; Lanius R.A	Classifying heterogeneous presentations of PTSD via the default mode, central executive, and salience networks with machine learning	NeuroImage: Clinical	2020
Eyigoz E.; Mathur S.; Santamaria M.; Cecchi G.; Naylor M	Linguistic markers predict onset of Alzheimer's disease	EClinicalMedicine	2020
Chen T.; Chen Y.; Yuan M.; Gerstein M.; Li T.; Liang H.; Froehlich T.; Lu L	The development of a practical artificial intelligence tool for diagnosing and evaluating autism spectrum disorder: Multicenter study	JMIR Medical Informatics	2020
Gao X.; Yan X.; Gao P.; Gao X.; Zhang S	Automatic detection of epileptic seizure based on approximate entropy, recurrence quantification analysis and convolutional neural networks	Artificial Intelligence in Medicine	2020
Wu C.-S.; Kuo C.-J.; Su C.-H.; Wang S.H.; Dai H.-J	Using text mining to extract depressive symptoms and to validate the diagnosis of major depressive disorder from electronic health records	Journal of Affective Disorders	2020
Li C.; Gheorghe D.A.; Gallacher J.E.; Bauermeister S	Psychiatric comorbid disorders of cognition: a machine learning approach using 1175 UK Biobank participants	Evidence-Based Mental Health	2020
Ucuz İ.; Özel Özcan Ö.; Mete B.; Ari A.; Kayhan Tetik B.; Yildirim K	Evaluation of inflammatory markers in childhood-onset psychiatric disorders by using artificial intelligence architectures; [Çocukluk çağı başlangıçlı psikiyatrik hastalıklarda yapay zeka mimarileri ile inflamatuvar değerlendirme]	Anadolu Psikiyatri Dergisi	2020
Pavlacic J.M.; Young J	Process-Based Cognitive Behavioral Therapy: A Framework for Conceptualization and Treatment	Clinical Case Studies	2020
Greenman D.L.B.; La M.A.N.; Shah S.; Chen Q.; Berman K.F.; Weinberger D.R.; Tan H.Y	Parietal-prefrontal feedforward connectivity in association with schizophrenia genetic risk and delusions	American Journal of Psychiatry	2020
Walsh-Messinger J.; Jiang H.; Lee H.; Rothman K.; Ahn H.; Malaspina D	Relative importance of symptoms, cognition, and other multilevel variables for psychiatric disease classifications by machine learning	Psychiatry Research	2019
Wang A.D.; Leong M.; Johnstone B.; Rayner G.; Kalincik T.; Roos I.; Kwan P.; O'Brien T.J.; Velakoulis D.; Malpas C.B	Distinct psychopathology profiles in patients with epileptic seizures compared to non-epileptic psychogenic seizures	Epilepsy Research	2019
Fu C.H.Y.; Fan Y.; Davatzikos C	Addressing heterogeneity (and homogeneity) in treatment mechanisms in depression and the potential to develop diagnostic and predictive biomarkers	NeuroImage: Clinical	2019

Table 1 (continued)

Authors	Title	Journal	Year
Tuncer T.; Dogan S.; Akbal E	A novel local senary pattern based epilepsy diagnosis system using EEG signals	Australasian Physical and Engineering Sciences in Medicine	2019
Sheibani R.; Nikookar E.; Alavi S	An ensemble method for diagnosis of Parkinson's disease based on voice measurements	Journal of Medical Signals and Sensors	2019
Rios-Urrego C.D.; Vásquez-Correa J.C.; Vargas-Bonilla J.F.; Nöth E.; Lopera F.; Orozco-Arroyave J.R	Analysis and evaluation of handwriting in patients with Parkinson's disease using kinematic, geometrical, and non-linear features	Computer Methods and Programs in Biomedicine	2019
Stoyanov D.; Kandilarova S.; Paunova R.; Barranco Garcia J.; Latypova A.; Kherif F	Cross-Validation of Functional MRI and Paranoid-Depressive Scale: Results From Multivariate Analysis	Frontiers in Psychiatry	2019
Armanious K.; Küstner T.; Reimold M.; Nikolaou K.; La Fougère C.; Yang B.; Gatidis S	Independent brain 18F-FDG PET attenuation correction using a deep learning approach with Generative Adversarial Networks	Hellenic journal of nuclear medicine	2019
Usta M.B.; Karabekiroglu K.; Sahin B.; Aydin M.; Bozkurt A.; Karaosman T.; Aral A.; Cobanoglu C.; Kurt A.D.; Kesim N.; Sahin İ.; Ürer E	Use of machine learning methods in prediction of short-term outcome in autism spectrum disorders	Psychiatry and Clinical Psychopharmacology	2019
Subasi A.; Ahmed A.; Aličković E.; Rashik Hassan A	Effect of photic stimulation for migraine detection using random forest and discrete wavelet transform	Biomedical Signal Processing and Control	2019
Garb H.N.; Wood J.M	Methodological advances in statistical prediction	Psychological Assessment	2019
van Leeuwen K.G.; Sun H.; Tabaeizadeh M.; Struck A.F.; van Putten M.J.A.M.; Westover M.B	Detecting abnormal electroencephalograms using deep convolutional networks	Clinical Neurophysiology	2019
Zhutovsky P.; Vijverberg E.G.B.; Bruin W.B.; Thomas R.M.; Wattjes M.P.; Pijnenburg Y.A.L.; Van Wingen G.A.; Dols A	Individual Prediction of Behavioral Variant Frontotemporal Dementia Development Using Multivariate Pattern Analysis of Magnetic Resonance Imaging Data	Journal of Alzheimer's Disease	2019
Illavarason P.; Arokia Renjit J.; Mohan Kumar P	Medical Diagnosis of Cerebral Palsy Rehabilitation Using Eye Images in Machine Learning Techniques	Journal of Medical Systems	2019
Portugal L.C.L.; Schrouff J.; Stiffler R.; Bertocci M.; Bebko G.; Chase H.; Lockovitch J.; Aslam H.; Graur S.; Greenberg T.; Pereira M.; Oliveira L.; Phillips M.; Mourão-Miranda J	Predicting anxiety from wholebrain activity patterns to emotional faces in young adults: a machine learning approach	NeuroImage: Clinical	2019
Tan J.; Rollins C.P.E.; Israel S.; Benrimoh D	Primed for Psychiatry: The role of artificial intelligence and machine learning in the optimization of depression treatment	University of Toronto Medical Journal	2019
Salazar-Muñoz Y.; López-Pérez G.A.; García-Caballero B.E.; Muñoz-Rios R.; Ruano-Calderón L.A.; Trujillo L	Classification and Assessment of the Patelar Reflex Response through Biomechanical Measures	Journal of Healthcare Engineering	2019
Amoroso N.; La Rocca M.; Monaco A.; Bellotti R.; Tangaro S	Complex networks reveal early MRI markers of Parkinson's disease	Medical Image Analysis	2018
Khanmohammadi S.; Chou C.-A	Adaptive Seizure Onset Detection Framework Using a Hybrid PCA-CSP Approach	IEEE Journal of Biomedical and Health Informatics	2018
Kaya Y.; Ertuğrul Ö.F	A stable feature extraction method in classification epileptic EEG signals	Australasian Physical and Engineering Sciences in Medicine	2018

Table 1 (continued)

Authors	Title	Journal	Year
Jauhar S.; Krishnadas R.; Nour M.M.; Cunningham-Owens D.; Johnstone E.C.; Lawrie S.M	Is there a symptomatic distinction between the affective psychoses and schizophrenia? A machine learning approach	Schizophrenia Research	2018
Yang H.; Zhang J.; Liu Q.; Wang Y	Multimodal MRI-based classification of migraine: Using deep learning convolutional neural network 08 Information and Computing Sciences 0801 Artificial Intelligence and Image Processing	BioMedical Engineering Online	2018
Bruffaerts R	Machine learning in neurology: what neurologists can learn from machines and vice versa	Journal of Neurology	2018
Acharya U.R.; Oh S.L.; Hagiwara Y.; Tan J.H.; Adeli H.; Subha D.P	Automated EEG-based screening of depression using deep convolutional neural network	Computer Methods and Programs in Biomedicine	2018
Balakrishnan P.; Hemalatha S.; Keshav D.N.S	Detection of Startle-Type Epileptic Seizures using Machine Learning Technique	International Journal of Epilepsy	2018
Zheng H.; Zheng P.; Zhao L.; Jia J.; Tang S.; Xu P.; Xie P.; Gao H	Predictive diagnosis of major depression using NMR-based metabolomics and least-squares support vector machine	Clinica Chimica Acta	2017
Galatzer-Levy I.R.; Ma S.; Statnikov A.; Yehuda R.; Shalev A.Y	Utilization of machine learning for prediction of post-traumatic stress: A re-examination of cortisol in the prediction and pathways to non-remitting PTSD	Translational Psychiatry	2017
Taylor J.A.; Matthews N.; Michie P.T.; Rosa M.J.; Garrido M.I	Auditory prediction errors as individual biomarkers of schizophrenia	NeuroImage: Clinical	2017
Cui G.; Xia L.; Tu M.; Liang J	Automatic classification of epileptic electroencephalogram based on multiscale entropy and extreme learning machine	Journal of Medical Imaging and Health Informatics	2017
Ho L.; Legere M.; Li T.; Levine S.; Hao K.; Valcarcel B.; Pasinetti G.M	Autonomic nervous system dysfunctions as a basis for a predictive model of risk of neurological disorders in subjects with prior history of traumatic brain injury: implications in Alzheimer's disease	Journal of Alzheimer's Disease	2017
O'Halloran R.; Kopell B.H.; Sprooten E.; Goodman W.K.; Frangou S	Multimodal neuroimaging-informed clinical applications in neuropsychiatric disorders	Frontiers in Psychiatry	2016
Bone D.; Bishop S.L.; Black M.P.; Goodwin M.S.; Lord C.; Narayanan S.S	Use of machine learning to improve autism screening and diagnostic instruments: effectiveness, efficiency, and multi-instrument fusion	Journal of Child Psychology and Psychiatry and Allied Disciplines	2016
Kassraian-Fard P.; Matthis C.; Balsters J.H.; Maathuis M.H.; Wenderoth N	Promises, pitfalls, and basic guidelines for applying machine learning classifiers to psychiatric imaging data, with autism as an example	Frontiers in Psychiatry	2016
Chen S.-J.; Liao D.-L.; Shen T.-W.; Yang H.-C.; Chen K.-C.; Chen C.-H	Genetic signatures of heroin addiction	Medicine (United States)	2016
Peker M.; Şen B.; Delen D	Computer-aided diagnosis of Parkinson's disease using complex-valued neural networks and mRMR feature selection algorithm	Journal of Healthcare Engineering	2015

Table 1 (continued)

Authors	Title	Journal	Year
Karstoft K.-I.; Galatzer-Levy I.R.; Statnikov A.; Li Z.; Shalev A.Y.; Ankri Y.; Freedman S.; Addesky R.; Israeli-Shalev Y.; Gilad M.; Roitman P	Bridging a translational gap: Using machine learning to improve the prediction of PTSD	BMC Psychiatry	2015
Matthews M.; Fair D.A	Research Review: Functional brain connectivity and child psychopathology—Overview and methodological considerations for investigators new to the field	Journal of Child Psychology and Psychiatry and Allied Disciplines	2015
Tekin Erguzel T.; Tas C.; Cebi M	A wrapper-based approach for feature selection and classification of major depressive disorder-bipolar disorders	Computers in Biology and Medicine	2015
Tucker C.; Han Y.; Black Nembhard H.; Lee W.-C.; Lewis M.; Sterling N.; Huang X	A data mining methodology for predicting early stage Parkinson's disease using non-invasive, high-dimensional gait sensor data	IIE Transactions on Healthcare Systems Engineering	2015
Kessler R.C.; Warner C.H.; Ivany C.; Petukhova M.V.; Rose S.; Bromet E.J.; Brown M., III; Cai T.; Colpe L.J.; Cox K.L.; Fullerton C.S.; Gilman S.E.; Gruber M.J.; Heeringa S.G.; Lewandowski-Romps L.; Li J.; Millikan-Bell A.M.; Naifeh J.A.; Nock M.K.; Rosellini A.J.; Sampson N.A.; Schoenbaum M.; Stein M.B.; Wessely S.; Zaslavsky A.M.; Ursano R.J	Predicting suicides after psychiatric hospitalization in US army soldiers: The Army Study to Assess Risk and Resilience in Servicemembers (Army STARRS)	JAMA Psychiatry	2015
Pradhan C.; Wuehr M.; Akrami F.; Neuhaeusser M.; Huth S.; Brandt T.; Jahn K.; Schniepp R	Automated classification of neurological disorders of gait using spatio-temporal gait parameters	Journal of Electromyography and Kinesiology	2015
Martinelli C.; Shergill S.S	Everything you wanted to know about neuroimaging and psychiatry, but were afraid to ask	BJ Psych Advances	2015
Zeng L.-L.; Shen H.; Liu L.; Hu D	Unsupervised classification of major depression using functional connectivity MRI	Human Brain Mapping	2014
Sundermann B.; Herr D.; Schwindt W.; Pfleiderer B	Multivariate classification of blood oxygen level-dependent fMRI data with diagnostic intention: A clinical perspective	American Journal of Neuroradiology	2014
Singh N.; Thomas Fletcher P.; Samuel Preston J.; King R.D.; Marron J.S.; Weiner M.W.; Joshi S	Quantifying anatomical shape variations in neurological disorders	Medical Image Analysis	2014
Eickhoff S.B.; Bzdok D	Neuroimaging and modeling: Where is the road to clinical application?	Psychiatrie	2014

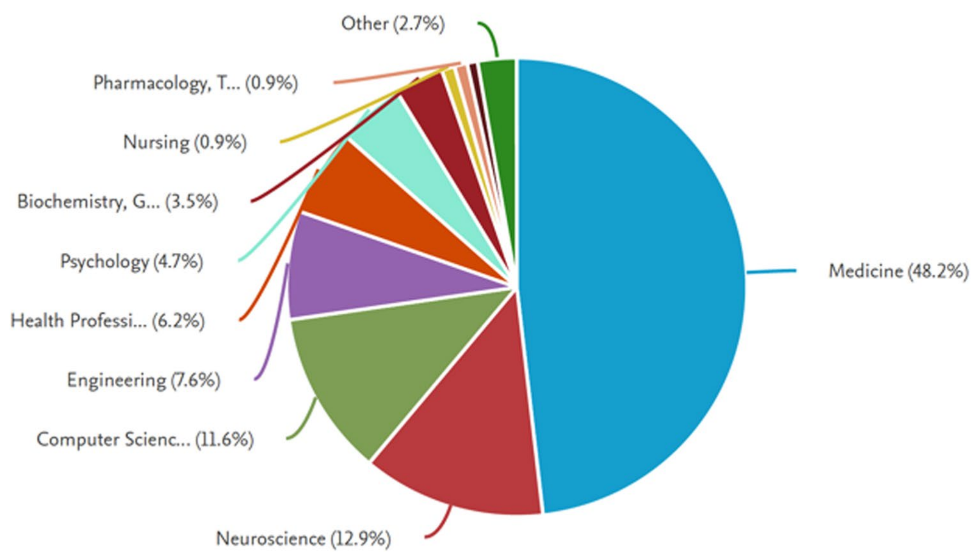


Fig. 2 Composition of Scopus articles based on the subject area. The image is taken directly from the "Analyze Results" function of Scopus

5.4 Data preprocessing

The bibliographic data were exported from Scopus in CVS format and imported into VOSviewer, a software tool for constructing and visualising bibliometrics networks.

For term mapping and network visualisation, clustering was performed using VOSviewer's clustering algorithm with default parameters.

5.5 Data analysis and visualization

The analysis focused on:

Publication trends over time.
Geographical contributions based on authors' affiliations.
Main publication venues (journals, institutions)
Disorder classification.
Algorithms' frequency of use.

The top 10 most cited papers were selected for deeper examination of: algorithms, evaluation metrics, and challenges addressed.

5.6 Evaluation metrics used in selected studies

To address RQ6, we extracted the evaluation metrics reported in the most-cited studies, these included:

Accuracy.
Precision and recall.
F1-score.
Area under the curve.
Sensitivity and specificity.

These metrics offer insight about how AI tools are validated in real-world diagnostic scenarios.

6 Results

In this section, the research results will be presented, providing an answer to the first four research questions.

RQ1 How many scientific studies have been published between 2014 and 2024 regarding the use of the use of AI-driven diagnostic methods?

This research question aimed to quantify the scientific community's interest in utilising AI for the early diagnosis of neurodegenerative diseases and psychopathologies. As depicted by Fig. 3, the number of publications within this domain has shown a consistent upward trajectory from 2014 to 2024. The number of publications rose from 4 in 2014 to 64 in 2024. This growth indicates a growing interest in the use of ML and DL to support early diagnosis of diseases that represent a significant burden on society.

RQ2 What are the most relevant research centers for studies on AI for the diagnosis of mental and neurological disorders?

This research question sought to identify leading research centers contributing to the dissemination of knowledge on AI applications in diagnosis. The findings, visualized in Fig. 4, highlight the institutions with the highest impact and publication output in this area. In particular, King's College is the leading institution with the highest number of publications.

RQ3 Which countries had the most active research centers?

This question focuses on the geographical distribution of research activity. As shown in Fig. 5 the United States leads in term of publication output, followed by China, the United Kingdom, Germany and Canada. Additional contributors include Italy, India, Australia, Turkey and Netherlands, underscoring a global effort in advancing AI for diagnostic purposes. Figure 6 represents a VOSviewer map of the collaboration between different countries in conducting studies.

RQ4 In which disorder is AI most commonly applied?

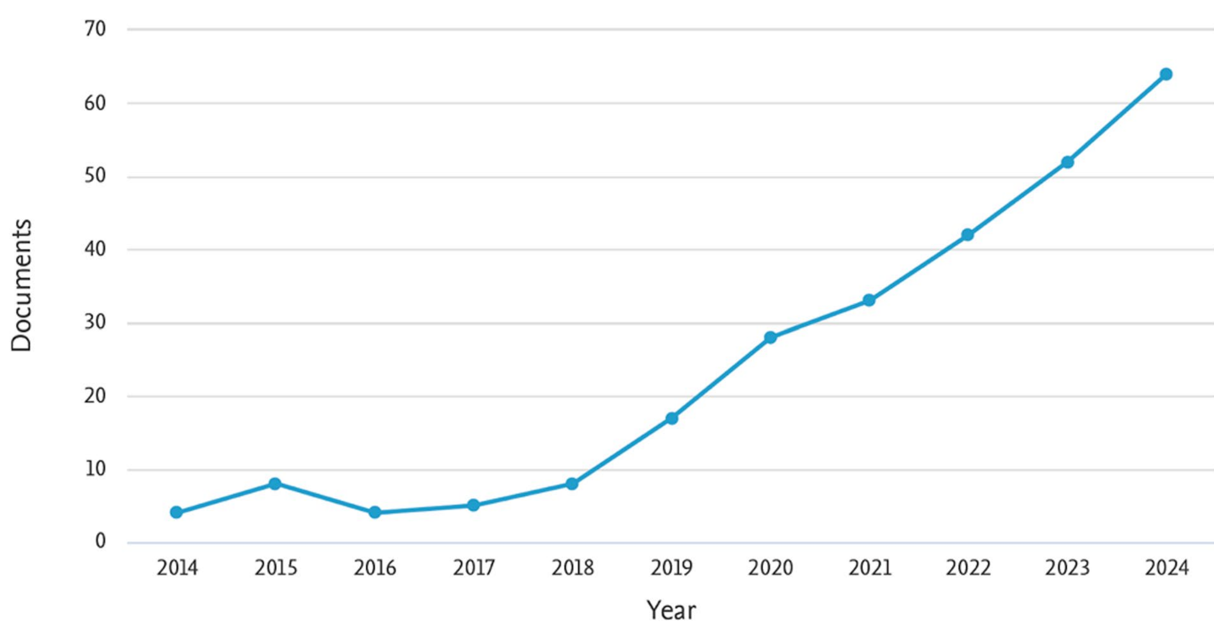


Fig. 3 Academics studies published from 2014 to 2024 in Scopus database. The image is taken directly from the "Analyze Results" function of Scopus

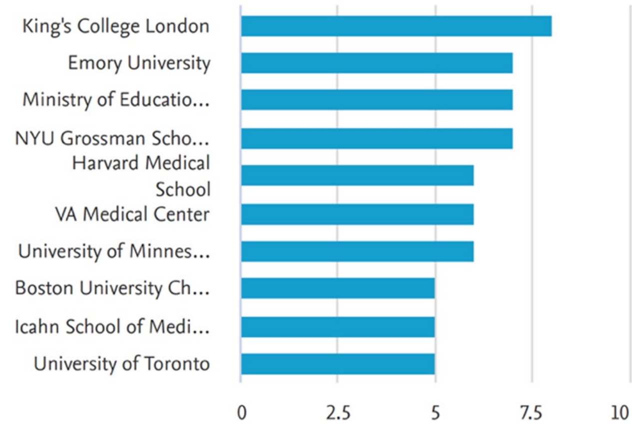


Fig. 4 Institutions where most of the research was conducted. At the bottom the number of articles is displayed, while on the left there is the name of the institute. The image is taken directly from the "Analyze Results" function of Scopus

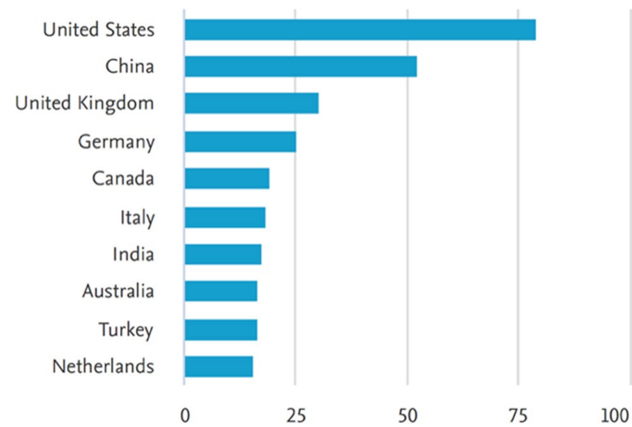


Fig. 5 Number of publications for each country. At the bottom there is the number of publications, while on the left there are the most involved countries. The image is taken directly from the "Analyze Results" function of Scopus

This research question aims to find the primary neurological and psychiatric diseases for which AI-driven diagnostic tools are frequently utilised. To conduct this investigation, we analysed the keywords from the 265 considered articles, as shown in Fig. 7.

Among them, there is a clear predominance of depressive disorder, followed by an equal distribution between various neurodegenerative diseases and psychiatric disorders. Bibliometric analysis of the co-occurrence of the keywords found in the index (Fig. 8) and co-autorship (Fig. 9) were then carried out using VOSviewer.

7 Analysis of the main papers

In this section, we analyse the 10 most cited articles from the final database, following to the selection criteria outlined in Sect. 5. A comprehensive overview is shared, highlighting the key areas of interest in the selected articles on the application of AI to diagnose both neurological and mental disorders. First, the most commonly used algorithms in this field will be listed and briefly explained, addressing research question number 5 (RQ5). Next, the metrics used to evaluate the performances of the aforementioned algorithms will be indicated (RQ6). Finally, the primary challenges faced in the selected articles will be discussed (RQ7).

In Fig. 10, the following information is given for each article: the title (first column), the year of publication (second column), the number of citations (third column), the method underlying the proposed technique (fourth column), and the dataset utilised for the analyses (fifth column). Where specific details are not provided, these are marked as "N/A".

RQ5 Which AI algorithms have been most commonly used to diagnose both neurological and mental disorders?

This research question aims to offer professionals with a clear understanding of the algorithmic techniques applied in this field, as discussed in the selected studies. To this end, the technical aspects of each document are examined, including the algorithms employed and the datasets used. The most frequently employed techniques are outlined below:

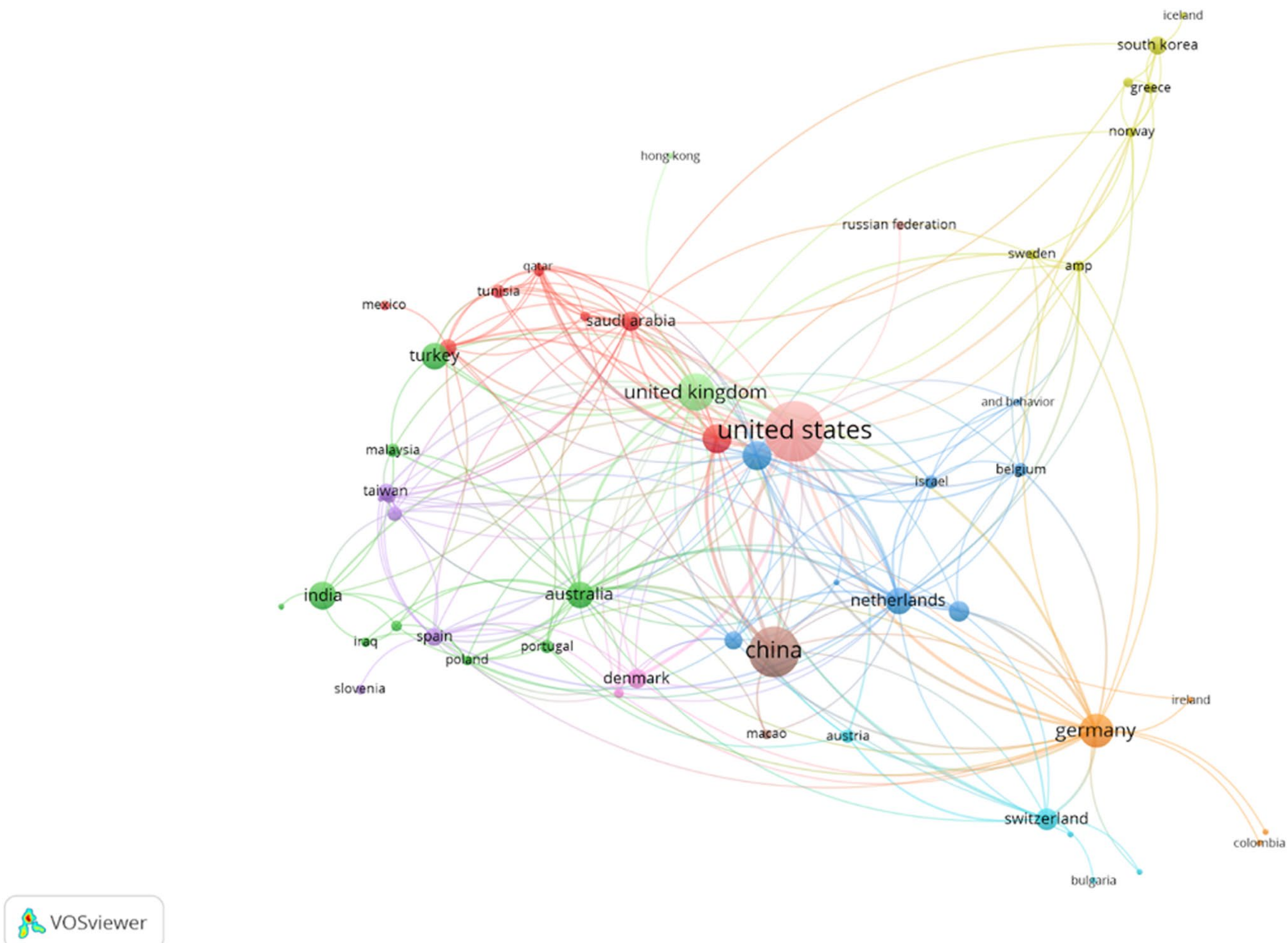
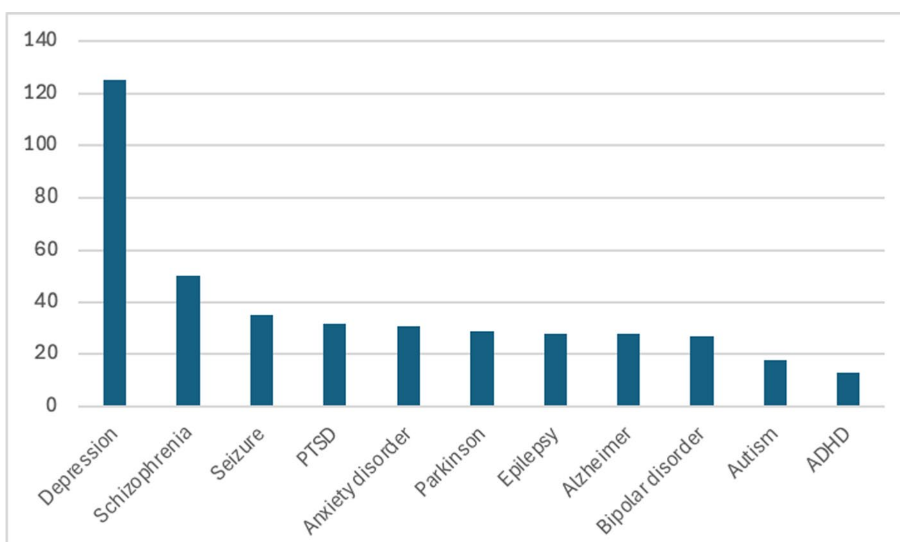


Fig. 6 Bibliometric analysis of collaboration between different countries in the publication of articles. The image was generated with VOSviewer

Fig. 7 Fields of application of AI in the diagnosis of psychiatric and neurological diseases, according to the Scopus database



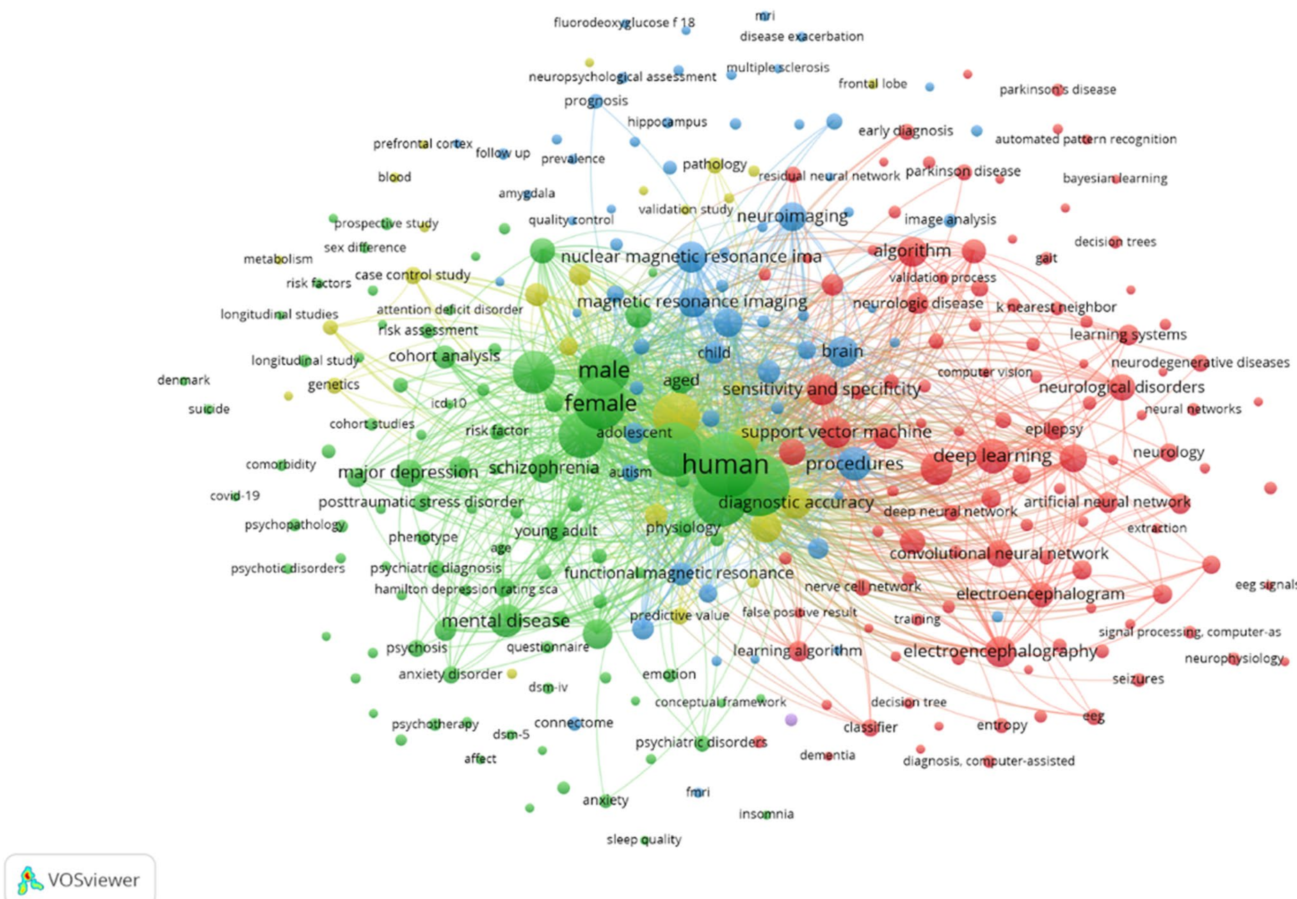


Fig. 8 Bibliometric analysis on the co-occurrence of the index keywords. Co-occurrence consists in the in the contemporary appearance of two keywords in the same article. In the diagram, each cluster is represented by a colour, and each element within a cluster shares the same colour. The size of the circle and label is determined by the frequency of the keyword's appearance. Each cluster groups keywords that describe an application domain of artificial intelligence in the medical field, and the lines connecting the elements represent the co-occurrence of keywords within an article

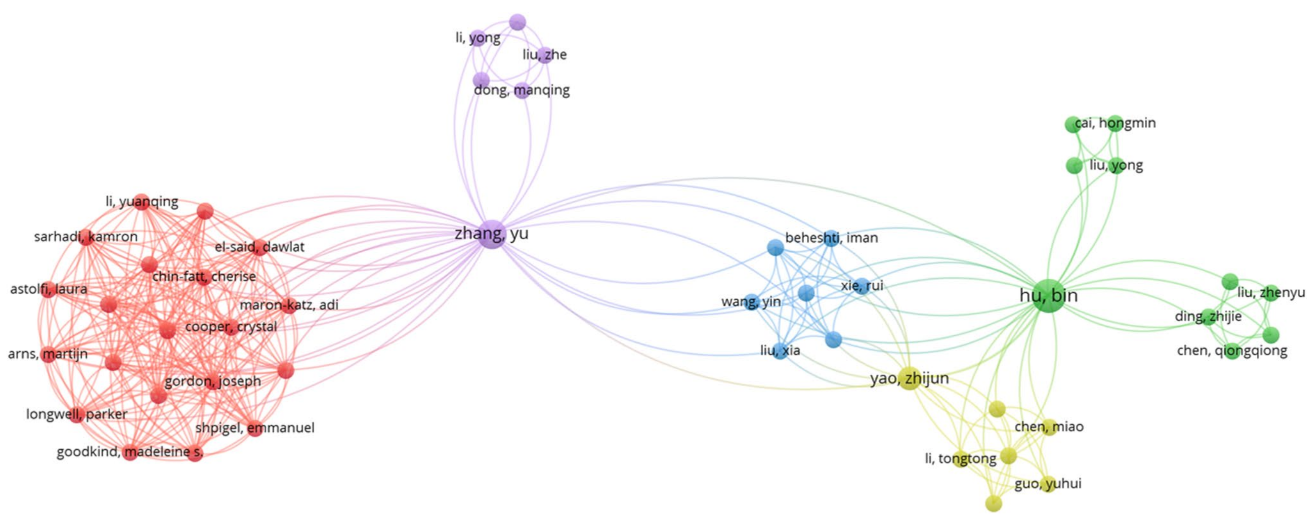


Fig. 9 Bibliometric analysis on the co-authorships generated with VOSviewer. The graph shows the collaboration relationships among authors of scientific articles with fewer than 25 co-authors. All articles were included, even those with only one citation, while authors without connections are not displayed. The nodes represent individual authors, and the size of the nodes reflects the number of associated publications. The lines indicate co-authorship between two authors. The different colors represent clusters automatically identified by VOSviewer, suggesting distinct research groups or communities with closer collaboration

Paper	Year	Citations	Methods	Dataset
Automated EEG-based screening of depression using convolutional neural network [45]	2018	447	CNN	Psychiatry Department, Medical College, Calicut, Kerala, India
Predicting suicides after psychiatric hospitalization in US army soldiers; The Army Study to Assess Risk and Resilience in Servicemembers (Army STARRS) [46]	2015	335	Regression trees, Elastic net regression	HADS (historical administrative data system) of the Army STARRS (army study to assess risk and resilience in servicemembers)
Unsupervised classification of major depression using functional connectivity MRI [47]	2014	153	MMC	First Affiliated Hospital of China Medical University and healthy
Use of machine learning to improve autism screening and diagnostic instruments: effectiveness, efficiency, and multi-instrument fusion [48]	2016	137	SVM	Balanced Independent Dataset
Bridging a translational gap: Using machine learning to improve the prediction of PTSD [49]	2015	121	SVM	Jerusalem Trauma Outreach and Prevention Study
Prevalence and Diagnosis of Neurological Disorders Using Different Deep Learning Techniques: A Mate-Analysis [50]	2020	111	CNN, DNN, RNN	N/A
Utilization of machine learning for prediction of post-traumatic stress: A re-examination of cortisol in the prediction and pathways to non-remitting PTSD [61]	2017	111	LGMM, SVM	N/A
Complex networks reveal early MRI markers of Parkinsons disease [54]	2018	105	Random forest, SVM	Parkinson's progression markers initiative (PPMI)
Identification of psychiatric disorder subtypes from functional connectivity patterns in resting-state electroencephalography [20]	2021	104	Sparse K-means	N/A
Linguistic markers predict onset of Alzheimer disease [55]	2020	101	SVM, logistic regression, naïve bayes classifiers	Framing heart study (FHS)

Fig. 10 Schematic summary of the content of the 10 most cited papers. The first column contains the title of the articles, the second the year of publication, the third the number of citations, the fourth the model used and the fifth the origin of the datasets used

Support vector machine (SVM):

SVM is a machine learning algorithm widely used for classification problems due to its simplicity and flexibility. It learns from examples to categorize or classify objects. Basically, the primary goal of SVMs is to determine a Hyperplane that effectively separates data points belonging to different classes. The chosen hyperplane is the one that maximises the distance between the hyperplane and the closest data points from each class. Recently, SVM has been employed to accurately predict diagnosis and prognosis of brain and psychiatric disorders, including Alzheimer's disease, schizophrenia and depression [36, 37].

Convolutional neural network (CNN):

A CNN is a type of artificial neural networks designed to simulate the human visual process. It consists of artificial neurons that handle inputs through various operations across multiple layers. In particular, it applies convolutional filters to input data to detect features and hierarchically learns more complex patterns through multiple layers. CNNs and are widely used in machine learning due to their numerous applications, such as facial recognition, image and video analysis, handwriting recognition, anomaly detection, drug discovery and voice recognition [38].

Logistic regression:

Logistic regression is a statistical method used to predict binary outcomes (e.g., diseased/ healthy) based on one or more independent variables. It is widely used in healthcare research for decision-making models and disease state prediction. Logistic regression relies on maximum likelihood estimation and thus requires large sample size to ensure sufficient representation across outcome categories [39].

RQ6 What metrics were used to evaluate performance of the identified AI tools?

Paper	Metrics	Challenges
Automated EEG-based screening of depression using convolutional neural network [45]	Accuracy, sensitivity, specificity	Develop a self-learning model to diagnose depression through EEG analysis
Predicting suicides after psychiatric hospitalization in US army soldiers; The Army Study to Assess Risk and Resilience in Servicemembers (Army STARRS) [46]	AUC, concentration of risk (CR)	Develop a more effective and reliable algorithm to predict suicide risk among US army soldiers
Unsupervised classification of major depression using functional connectivity MRI [47]	Clustering and classification consistency	Develop an unsupervised ML approach using fMRI scans to improve objectivity of diagnosing MDD
Use of machine learning to improve autism screening and diagnostic instruments: effectiveness, efficiency, and multi-instrument fusion [48]	Unweighted average recall (UAR)	Create robust ML algorithms to enhance the accuracy and efficiency of ASD diagnoses
Bridging a translational gap: Using machine learning to improve the prediction of PTSD [49]	Accuracy, sensitivity, specificity, AUC	Enhance the personalization of PTSD risk prediction using ML, to analyze less obvious predictive factors
Prevalence and Diagnosis of Neurological Disorders Using Different Deep Learning Techniques: A Mate-Analysis [50]	Accuracy, sensitivity, specificity	Review the use of DL techniques for early diagnosis of neurological and psychiatric disorders
Utilization of machine learning for prediction of post-traumatic stress: A re-examination of cortisol in the prediction and pathways to non-remitting PTSD [51]	Accuracy, sensitivity, specificity, positive predictive value, AUC	Develop predictive models to classify individuals at risk for PTSD through neuroendocrine responses
Complex networks reveal early MRI markers of Parkinson' s disease [54]	Accuracy, sensitivity, specificity, AUC	Propose a novel early diagnosis strategy for detecting Parkinson's disease prior to motor symptoms onset
Identification of psychiatric disorder subtypes from functional connectivity patterns in resting-state electroencephalography [20]	Accuracy, sensitivity, AUC	Identify subtypes of psychiatric disorders using ML techniques to analyze patterns from EEG data
Linguistic markers predict onset of Alzheimer disease [55]	Accuracy, sensitivity, specificity, positive predictive value, AUC	Predict the future onset of Alzheimer's disease in healthy individuals using automated linguistic analysis

Fig. 11 Schematic representation of the results of the 10 most cited papers' analysis. The first column presents the papers' titles, the second the metrics employed to evaluate the models' performances and the third summarises the challenges addressed by the studies

The aim of this research question is to offer an overview of the metrics used to evaluate the performance of the algorithms extracted from the 10 selected articles. The second column of Fig. 11 lists the metrics associated with the respective studies. The most commonly employed metrics include the following:

Accuracy:

Accuracy measures the predictive ability of a classification algorithm on the testing data, independent of decision biases or prior probabilities, thus allowing the performance of multiple systems to be compared on a common, interpretable scale. Valid and precise assessments of intrinsic accuracy enable users to determine the reliability of diagnostic tools. [40, 41]

Area Under the Curve (AUC):

AUC evaluates a classification algorithm's ability to produce probability estimates rather than solely class predictions. Thus, this metric is more sensitive than accuracy because it is independent of decision thresholds and class distributions. AUC has therefore been shown to be a superior discriminative indicator in numerous applications and statistical tests [42].

Sensitivity:

Sensitivity, also known as the true positive rate, represents the probability of obtaining a positive result among individuals who actually have the target condition. It reflects the ability of a test to detect true positives (e.g., diseased individuals) [43, 44].

$$TP/(TP + TN)$$

Specificity:

Specificity, also known as the true negative rate, represents the probability of obtaining a negative result among individuals who do not have the target condition. It indicates the ability of a test to detect true negatives (e.g., healthy subjects) [43, 44].

$$TN/(TN + FP)$$

Positive predictive value (PPV):

PPV represents the likelihood that a positive test result corresponds to the target condition. Furthermore, by indicating the portion of true positives among positive results, it helps assess a test's comparability to the 'gold standard' [43, 44].

$$TP/(TP + FP)$$

The metrics described above are those utilised in the 10 articles extracted that underwent in-depth analysis. Consequently, it is possible that other metrics may be used in additional studies within the database, depending on the context and objectives of the research.

RQ7 What challenges have been addressed in the development and implementation of AI-driven diagnostic methods?

The integration of AI in the medical field has challenged the traditional approaches to patient care, encompassing diagnosis, treatment and management of pathologies. However, the advent of personalized care has encountered obstacles, including ethical concerns, technical challenges, privacy-related issues, and acceptance by patients and healthcare professionals. To emphasize the importance of the challenges associated with implementing AI-driven diagnostic tools, we analysed the 10 most cited articles from the identified database. These articles were examined to determine how they address specific challenges in the context of AI applications to neurological and mental disorders. In the third column of Fig. 11, the challenges discussed in these articles are summarised in relation to the specific goals and context of each document. Detailed descriptions of the articles are given below:

Acharya et Al. [45] tackles the challenge of diagnosing depression, a condition that often goes undetected despite the availability of effective treatments. The article presents a self-learning model that can detect distinctive features in EEG data. The model was trained and tested on a self-made dataset made by EEG data collected from 15 healthy individuals and 15 depressed patients. The sampling rate of the signals was 256 Hz with a notch filter of 50 Hz to eliminate power line interference. The final dataset had 4348 records divided in half across the two populations of subjects. By creating a new dataset ad hoc for this task, the authors guaranteed a high level of data quality and heterogeneity. Subtle differences in brain activity between depressed and non-depressed individuals are identified through EEG analysis. In particular, EEG signals from the right hemisphere are more distinctive for diagnosing depression. This approach offers a clear advantage in terms of efficiency and improves sensitivity, specificity and accuracy of the diagnosis.

Kessler et Al. [46] explores a new approach to assess suicide risk among US Army soldiers within 12 months following treatment for a psychiatric disorder. The study addresses the challenge of accurately predicting suicide risk, a task that remains difficult despite known risk factors. The authors aim to overcome this limitation by developing a more effective and reliable risk prediction algorithm. To train and test it, the authors built their dataset starting from the Historical Administrative Data System of the Army Study to Assess Risk and Resilience in Servicemembers. This dataset had missing values, and it was inconsistent in some components probably because it wasn't created for research purposes. To ensure the reliability of the outputs, the remaining missing values were resolved using randomly selected multiple imputations and the inconsistencies were fixed with rational imputations.

Zeng et Al. [47] focuses on overcoming the limitations of traditional psychiatric diagnoses, particularly for Major Depressive Disorder (MDD), which often rely on self-reported symptoms and clinical observations that are susceptible to bias. The authors develop an unsupervised machine learning approach using fMRI scans, enabling classification without pre-labeled data, thus enhancing diagnostic objectivity. To do so, an ad hoc dataset was created, collecting the imaging scans of 24 patients diagnosed with Major Depressive Disorder and 29 healthy subjects. The healthy controls were selected on the basis of demographic similarity to each depressed patient. To avoid biases in the output, all patients underwent MRI under the same conditions and the scans were acquired and processed in the same manner. This research supports the application of machine learning in clinical practice, specifically reducing diagnostic bias and improving clinical outcomes.

In Bone et Al. [48] the objective is to create new diagnostic tools for Autism Spectrum Disorder (ASD) using ML techniques. The research aims to improve the performance of caregiver-report instruments to achieve the "gold-standard" diagnosis. The study seeks to develop robust ML algorithms that achieve efficiently event with datasets containing conflicting data, thereby contributing to more accurate and efficient diagnostic assessments for ASD. The dataset involved in the experiment included ADI-R and SRS scores for 1,264 verbal individuals with ASD and 462 with non-ASD developmental or psychiatric disorders and the subjects' data were drawn from an IRB approved repository.

Kartsoft et Al. [49] addresses the challenge of personalising PTSD diagnosis using ML techniques to analyse various combinations of predictive features. Unlike previous studies that focused on predictive factors in large groups, this research prioritises less obvious and less frequently recorded variables. The authors apply ML to a large dataset, utilizing support vector machines (SVM) to predict persistent PTSD symptoms. The dataset was made of data collected for the Jerusalem Trauma Outreach and Prevention Study. To predict PTSD symptoms trajectories, features about event characteristics, emergency department records and early symptoms were collected for 957 trauma survivors. This study aims to enhance the accuracy and personalization of PTSD risk prediction.

Gautam et Al. [50] aims to fill a gap in the existing literature by examining the use of DL techniques for the early diagnosis of neurological and psychiatric disorders, including cerebrovascular disease, Alzheimer's, Parkinson's, epilepsy, cerebral palsy, multiple sclerosis, autism and migraine. Given the complexity and severity of these diseases, which are often chronic and have poor prognosis, timely and accurate diagnosis is crucial. The article introduces various DL techniques and presents the major neurological disorders, analyzing the publication trends related to these conditions.

Galatzer-Levy et Al. [51] explores the use of advanced computational approaches to develop predictive models capable of classifying individuals with heterogeneous risk factors. In particular, they used the data collected by Shalev et al. (2008) [52] and Videlock et al. (2008) [53], two parts of a longitudinal study that, using classical GLM statistics, previously failed to show a group-wide association between endocrine markers at hospitalisation time and PTSD status 5 months later. The data included assessment of trauma exposure, personal information, neuroendocrine and psychiatric assessments of 152 patients. Notably, the neuroendocrine response, specifically cortisol, emergers as a stable predictor of the development of post-traumatic stress disorder (PTSD) when combined with other clinical data. The article emphasises early prediction and risk factor identification, suggesting that manipulating the mechanisms underlying the development of disorders can help prevent their onset.

Amoroso et Al. [54] propose a novel strategy for early diagnosis of Parkinson's disease (PD) prior to the manifestation of motor symptoms combining neural network and clinical features. The diagnostic tool is based exclusively on markers derived from MRI and uses an unsupervised methodology to model brain activity in both healthy subjects and patients to explore the brain areas most affected by the disease. To do so, the authors relied on data from the Parkinson's progressive markers initiative, both for clinical and imaging data. This online repository is strongly research oriented and very reliable. However, they do not specify the solutions adopted in the case of empty cells or inconsistent measurements. The author's approach focuses on the identification of a combination of different markers, enabling accurate early diagnosis and monitoring of disease progression.

Zhang et Al. [20] aims to identify existing subtypes of psychiatric disorders, such as post-traumatic stress disorder (PTSD) and major depressive disorder (MDD). The identification of these subtypes is conducted through an approach based on functional connectivity patterns, detected via resting-state EEG, and the application of machine learning techniques to identify solutions for connectivity-based diagnosis. To ensure output reliability, the data used to train and test the algorithms were collected specifically for this experiment.

In Eyigoz et Al. [55] aims to predict the future onset of Alzheimer's disease in cognitively normal subjects through automated linguistic analysis. The study used linguistic data to create predictive models and analyse the correlation between lower early-life linguistic performance and higher incidence of cognitive decline. The experiment relied on data collected by the Framingham heart study, a longitudinal study that tests cognitive status and its decline since 1975. Also in this case, the data source is reliable, but the authors did not reveal how they targeted inconsistent measurements. It emerges that language performance can reveal early signs of cognitive decline and thus be used as markers to identify at-risk individuals, enabling timely interventions.

8 Discussion

This document has investigated the scientific community's interest in the implementation of AI techniques, particularly machine learning, in the diagnosis neurological and mental disease over the past decade.

Our review of publications from 2014 to 2024 reveals a significant increase in research activity in this area. Specifically, the number of publications has risen from a minimal count to a substantial figure by 2024, highlighting the growing interest in using ML to support the early diagnosis of diseases.

The analysis focused on a total of 265 documents, selected based on inclusion and exclusion criteria, focusing exclusively to the medical domain. This final dataset was used to examine the evolution of publications, dissemination channels, the countries that contributed the most, and patterns of collaboration across research networks.

Lastly, to conduct a more in-depth analysis of our research, we selected the 10 most-cited articles, addressing the research questions defined previously.

The analysis underscores the growing interest of professionals in the development of new diagnostic methodologies. It is evident that AI is an important ally of the medical field in reducing the burden that these diseases impose on society. In particular, the results show that these technologies are help anticipate the diagnosis of the discussed pathologies.

Regarding neurodegenerative diseases, such as Alzheimer's, Parkinson's, and others, the primary objective is early diagnosis before the onset of debilitating symptoms. Early identification can prolong the patient's life enhancing its quality, reduce the burden on caregivers, and lessen the strain on the healthcare system. Although these diseases are chronic and progressive, it has been proven that the use of algorithms, which are fed clinical data, can predict the likelihood of disease onset and promote early management strategies.

In the field of psychiatric disorders, AI aims to improve quality of life and slow disease progression. Moreover, these algorithms have also proven crucial in identifying risk factors that may lead to severe consequences. In the case of post-traumatic stress disorder, these techniques have been able to identify warning signs for suicide risk, allowing for the monitoring of individuals and preventing tragic outcomes.

While the use of AI in diagnosis offers great potential, it also presents complex challenges and issues. The first hurdle to overcome is the acceptance of these technologies within the diagnostic process, both by healthcare professionals and, most importantly, by patients. Resistance to these technologies may be caused by a lack of trust or familiarity with their capabilities. Secondly, there are ethical and legal concerns, especially regarding accountability in the event of errors and the protection of patient privacy, given the vast volume of sensitive data required to enable these technologies to do their tasks.

Finally, data reliability and quality are also crucial challenges. The models are often trained on incomplete, biased, or low-quality data, which can lead to inaccurate or misleading diagnoses. Ensuring the integrity of training data is essential to the safe and effective use of these technologies.

At the end of this analysis, it is possible to state that the benefits of using these techniques are evident, while there are equally significant controversial aspects to consider. Rigorous approaches and close collaboration between developers, healthcare professionals and policymakers are essential to ensure AI as a supportive and safe tool in medical diagnosis.

9 Limitations and future directions

Despite the clear potential of artificial intelligence in the early diagnosis and management of psychiatric and neurological disorders, several critical limitations remain. First, is the issue of poor generalizability of the models, which are often developed using narrow and homogeneous datasets. This significantly reduces their applicability in real-world, heterogenous clinical settings. Another, major challenge is interpretability, as many algorithms operate as "black boxes", making it difficult for healthcare professionals to understand, and ultimately trust the decisions suggested by these systems. Additionally, the presence of bias in the training data can compromise both the fairness and reliability of the models.

To address these issues, future developments must focus on building large, shared, and representative dataset, as well as on developing interpretable models, for example through the use of explainable AI techniques. Although, none of the 10 most cited paper has implemented these kinds of techniques, recent studies have begun to embrace this direction, demonstrating how XAI can bridge the gap between model complexity and clinical interpretability, creating better healthcare solutions and enhancing models' accuracy [56]. For instance, Chadaga et al. (2023) [57] used advanced machine learning methods combined with explainable AI techniques to predict the efficacy of hematopoietic stem cell transplants in pediatric patients. The final model achieved excellent accuracy, and the use of XAI methods made it possible to explain predictions by identifying the most relevant variables, making the system interpretable and useful for supporting clinical decisions.

Similarly, another study applied multiple explainable AI approaches to predict stroke risk. XAI techniques highlighted key variables such as age, BMI, hypertension, average blood glucose levels, and hearth disease [58].

Again, Wani et al. (2024) [59] proposes a novel framework to classify subjects with cardiovascular diseases. This approach enhances DL's accuracy by integrating a XAI model that provides comprehensive explanations of the output at a global and local level. As a result, the model shows increased performances as compared to already existing models for this task, while assisting medical practitioners with their diagnostic procedure. Following the same approach, XAI has been proven useful in other branches of medicine, such as oncology. For instance, combining the efficacy of NNs with XAI explanations was demonstrated convenient for lung cancer detection [60] and to enhance breast cancer classification [61].

In the context of Alzheimer's detection, Goenka et al. (2024) [62] presented a deep learning-based classification model using 3D MRI images, which makes the process fully automated without the need for manual feature engineering. The system demonstrated notable accuracy in binary classification between affected patients and healthy controls, proving to be highly promising for clinical support in early Alzheimer's diagnosis.

Lastly, Goswani et al. (2024) [63] combined a deep neural network with XAI (Grad-CAM visualizations) to detect sickle cell disease from microscopic blood images, enhancing diagnostic precision while ensuring interpretability through visual cues. These examples illustrate how explainable AI can transform complex models into transparent, decision support tools in healthcare. Furthermore, promoting clinical studies will be essential to facilitate the integration of these new technologies into healthcare environments, with the goal of supporting, not replacing, clinical judgment.

The limitations highlighted by this research undoubtedly represent threats to validation. In particular, external validity is undermined, which poses a major issue: models fail to generalize to different clinical contexts or patient populations, limiting their applicability beyond the original study setting. This directly leads to a lack of clinical validation, as models that are not tested in real-world settings may not perform as expected in daily clinical practice, and it becomes impossible to determine whether they truly predict what they are intended to. Moreover, heterogeneous, poorly standardized data and the presence of bias can distort relationships between variables, introduce uncontrolled confounding factors, and threaten internal validity.

10 Conclusion

Our analysis highlights a growing use of AI-driven diagnostic methods. The impact of these new approaches has been evident in the last decade in both psychiatric and neurological diseases. Several methods have been proven useful from different points of views. Early diagnoses and risk factor identification are just two of the multiple challenges that can be addressed with AI-driven techniques. These new revolutionary approaches could lead to improve the intervention timing and to increase the quality of the patients' life, while reducing the caregiver's burden. A more personalized medicine and a more accurate and faster diagnosis are goals that emerge to be targeted by these recent developments. In this way, the healthcare system could improve the patient management and anticipate the treatment of a disease, avoiding tragic outcomes. However, alongside these promising developments, future research must investigate and address the limitations that have emerged from our research. Data reliability, privacy compliance and the presence of bias in the datasets are key aspects to target to enhance model reliability and to avoid inaccurate diagnoses. Furthermore, topics such as acceptability and explainability also need to be thoroughly investigated. Addressing these topics is essential to foster trust and confidence in AI-driven diagnostic methods. Only by overcoming these limitations will it be possible to fully realise the advantages that the development of AI in diagnostic can offer.

Author contributions The data retrieval and database analysis were carried out by both main authors, C.R and L.C. C. R. was responsible for writing the sections related to methodology, results, analysis of the main papers, and discussion. L. C. was responsible for writing the sections related to the introduction, machine learning and deep learning, related works, and conclusion. D. L.T. supervised the research of materials and the drafting of the work. All authors reviewed the manuscript.

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Data Availability Our data have been freely downloaded from Scopus using the keywords mentioned in the paper. The dataset used in our analysis can be easily replicated: https://www.scopus.com/search/form.uri?display = basic#basic.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing Interests The authors declare no competing interests.

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