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Review article

Diagnosis of mental disorders using machine learning: Literature review and bibliometric mapping from 2012 to 2023

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ABSTRACT

Background: Mental disorders (MDs) are becoming a leading burden in non-communicable diseases (NCDs). As per the World Health Organization's 2022 assessment report, there was a steep increase of 25 % in MDs during the COVID-19 pandemic. Early diagnosis of MDs can significantly improve treatment outcome and save disability-adjusted life years (DALYs). In recent times, the application of machine learning (ML) and deep learning (DL)) has shown promising results in the diagnosis of MDs, and the field has witnessed a huge research output in the form of research publications. Therefore, a bibliometric mapping along with a review of recent advancements is required.

Methods: This study presents a bibliometric analysis and review of the research, published over the last 10 years. Literature searches were conducted in the Scopus database for the period from January 1, 2012, to June 9, 2023. The data was filtered and screened to include only relevant and reliable publications. A total of 2811 journal articles were found. The data was exported to a comma-separated value (CSV) format for further analysis. Furthermore, a review of 40 selected studies was performed.

Results: The popularity of ML techniques in diagnosing MDs has been growing, with an annual research growth rate of 17.05 %. The Journal of Affective Disorders published the most documents (n = 97), while Wang Y. (n = 64) has published the most articles. Lotka's law is observed, with a minority of authors contributing the majority of publications. The top affiliating institutes are the West China Hospital of Sichuan University followed by the University of California, with China and the US dominating the top 10 institutes. While China has more publications, papers affiliated with the US receive more citations. Depression and schizophrenia are the primary focuses of ML and deep learning (DL) in mental disease detection. Co-occurrence network analysis reveals that ML is associated with depression, schizophrenia, autism, anxiety, ADHD, obsessive-compulsive disorder, and PTSD. Popular algorithms include support vector machine (SVM) classifier, decision tree classifier, and random forest classifier. Furthermore, DL is linked to neuroimaging techniques such as MRI, fMRI, and EEG, as well as bipolar disorder. Current research trends encompass DL, LSTM, generalized anxiety disorder, feature fusion, and convolutional neural networks.

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1. Introduction

Mental health is a global concern because mental health issues are on the rise globally. During the first year of the COVID-19 pandemic, cases of depression and anxiety increased by over 25 % [1]. As far as the diagnosis of mental disorders is concerned, it is done using some predefined criteria. Two widely recognized manuals are employed by mental health professionals worldwide for diagnosing various mental disorders: the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) and the International Classification of Diseases (ICD-11 Chapter 6) [2–4]. The DSM-5 is developed by the American Psychiatric Association, while the ICD-11 manual is designed by the World Health Organization. In many parts of the world, especially in developing countries, there is an acute shortage of trained mental health professionals and infrastructure to provide mental healthcare facilities [5,6]. The use of information and communication technologies (ICT) and artificial intelligence (AI) can help mental health professionals work effectively, attend to more patients, and make better decisions [7,8].

ML is a branch of artificial intelligence that involves the development of algorithms and statistical models that enable the performance of tasks without being explicitly programmed; by learning from data, identifying patterns, and making decisions or predictions based on the learned patterns [9,10]. Deep learning (DL) is a subset of machine learning that focuses on using neural networks with multiple layers (hence the term "deep") to learn complex patterns and representations from large amounts of data [11]. ML techniques have shown some promising results in extracting meaningful patterns and features from diverse data sources to facilitate the early detection, classification, and prediction of MDs [12–14]. Furthermore, DL, has received significant attention for its capability of automatically learning hierarchical representations from raw data, enabling the discovery of complex features and underlying relationships within mental health datasets [15,16]. ML-based predictive models have achieved success in identifying individuals at risk of developing mental health disorders [17,18], optimizing treatment plans based on individual characteristics [19–21], and predicting treatment response and long-term outcomes [22].

Bibliometric analysis is a process of quantitatively analyzing scientific and academic literature by using statistical techniques to measure patterns of publication outcome, authorship, and impact of the published documents in a given field [23,24]. Bibliometric analysis is helpful for deeper understanding and reviewing the literature in various fields, including healthcare informatics research [24]. Despite a vast amount of research in the field of machine learning-based mental disorder diagnosis, a bibliometric analysis and review of the topic are missing in the literature. The aim of the current study is to fill this gap and provide a timely bibliometric analysis and scoping review on ML and DL techniques for MD diagnosis, focusing exclusively on journal articles obtained from the Scopus database. Scopus is a widely recognized and comprehensive multidisciplinary repository, encompassing a vast collection of high-quality scientific literature. By restricting the analysis to journal articles, this study ensures a rigorous examination of peer-reviewed research, providing reliable and credible sources to explore the current state of the field accurately.

The present study has the following objectives.

- Evaluating research outcomes in the field of MD diagnosis using machine learning from 2012 to 2013.
- Assessing collaboration patterns among authors, institutions, and countries during this period.
- Analyzing the most cited documents pertaining to ML-based MD diagnosis.
- Conducting a keyword analysis to identify prevalent terms and concepts.
- Investigating research trends and clustering within the domain of machine learning for MD diagnosis.
- Conducting a literature survey to explore the utilization of ML techniques in diagnosing MDs during 2012–2013.

Furthermore, the work tries to find the answers to the following research questions.

- What are the publication trends in machine learning-based MD diagnosis from 2012 to 2013? Who are the most productive authors, and which sources publish these papers?
- What forms of collaboration exist among authors, institutions, and countries in research related to machine learning-based MD diagnosis during this period?
- Which keywords are most frequently used in the literature during 2012–2013, providing insights into prevalent themes?
- What are the emerging thematic areas and research trends in machine learning for MD diagnosis during the specified timeframe?
- Which MDs are most commonly addressed using ML/DL approaches during 2012–2013? What are the data modalities utilized, and what types of algorithms demonstrate promising performance in diagnosing mental disorders?

By encompassing both ML and DL approaches, this bibliometric analysis acknowledges the diverse methodologies employed in the field of MDs diagnosis. While traditional ML techniques offer interpretability and transparency [25,26], DL models excel at automatically learning complex patterns and representations from raw data [16,27]. Understanding the adoption, impact, and relative performance of different ML and DL methodologies within mental health research can guide the development of robust and reliable diagnostic tools.

Literature searches were conducted in the Scopus database for the period from January 1, 2012, to June 9, 2023. The data was further filtered to include only the English-language journal articles published during this period. A total of 2811 journal articles were found. The data was exported to a comma-separated value (CSV) format for further analysis. There is an increasing trend in research output in the area year over year. The findings of this review and bibliometric analysis will be useful for researchers and other stakeholders, interested in understanding the current landscape of ML and DL-based MDs diagnosis. The bibliometric mapping of the data will help understand the key trends, influential and productive authors, highly cited papers, and prominent journals. Moreover, it provides insights into the advancement of the field, identify knowledge gaps, and facilitate future collaborations and research initiatives.

The rest of the paper is organized as follows: Section 2 provides background and theoretical insights on the evolution of ML applications in MD diagnosis. Section 3 details the various materials and methods used for performing the bibliometric study and literature review. Section 4 presents the results of the bibliometric study. Section 5 presents a concise review of recent research in the field of ML for MDs diagnosis, wherein different approaches, data modalities, and strengths and weaknesses of various approaches for the diagnosis of a variety of MDs (divided into seven categories) have been discussed. Section 6 presents a critical discussion of the current findings in contrast to the prior research. Furthermore, the limitations and scope of the current study have been discussed in Section 7. Finally, Section 8 draws some conclusions, and at the end, appendix section and references have been given.

2. The evolution of ML applications in MDs diagnosis: background and theoretical insights

Fig. 1 shows the evolution of the application areas of ML and DL in mental disease detection. In the late 20th century, early applications of machine learning methods, such as linear discriminant analysis and support vector machines, naïve Bayes classifiers, and decision tree algorithms started finding applications in mental disease diagnosis, such as creating models for mental retardation [28] and improving psychological tests for disease detection [29]. These approaches were primarily applied to relatively simple datasets and focused on basic classification tasks, such as distinguishing between different diagnostic categories based on structured clinical data.

The early 2000s witnessed a surge in the application of machine learning techniques to neuroimaging data for the diagnosis and characterization of mental disorders [30–32]. Studies began to use techniques like voxel-based morphometry (VBM), functional connectivity analysis, and pattern recognition algorithms to identify brain biomarkers associated with conditions like schizophrenia, depression, and Alzheimer's disease.

The 2010s saw the rise of deep learning techniques, particularly convolutional neural networks (CNN) and recurrent neural networks (RNN), which revolutionized the field of artificial intelligence, including mental health applications [33–35]. Deep learning models were applied to a wide range of data modalities, including neuroimaging, genetic, and behavioral data, enabling more sophisticated analyses and improved diagnostic accuracy. Deep learning-based approaches showed promise in tasks such as image classification from neuroimaging scans, prediction of treatment outcomes, and automated analysis of electronic health records [36, 37]. During the 2010s, the integration of digital health technologies and penetration of ML/DL models started taking place in the mental healthcare informatics. Smartphone apps, wearable devices, and remote monitoring systems, provided new opportunities for the application of machine learning in mental health [38]. Mobile apps and wearable devices began to collect various types of data, including physiological signals, activity levels, and social interactions, which could be analyzed using ML/DL algorithms to assess mental health status and detect early warning signs [39].

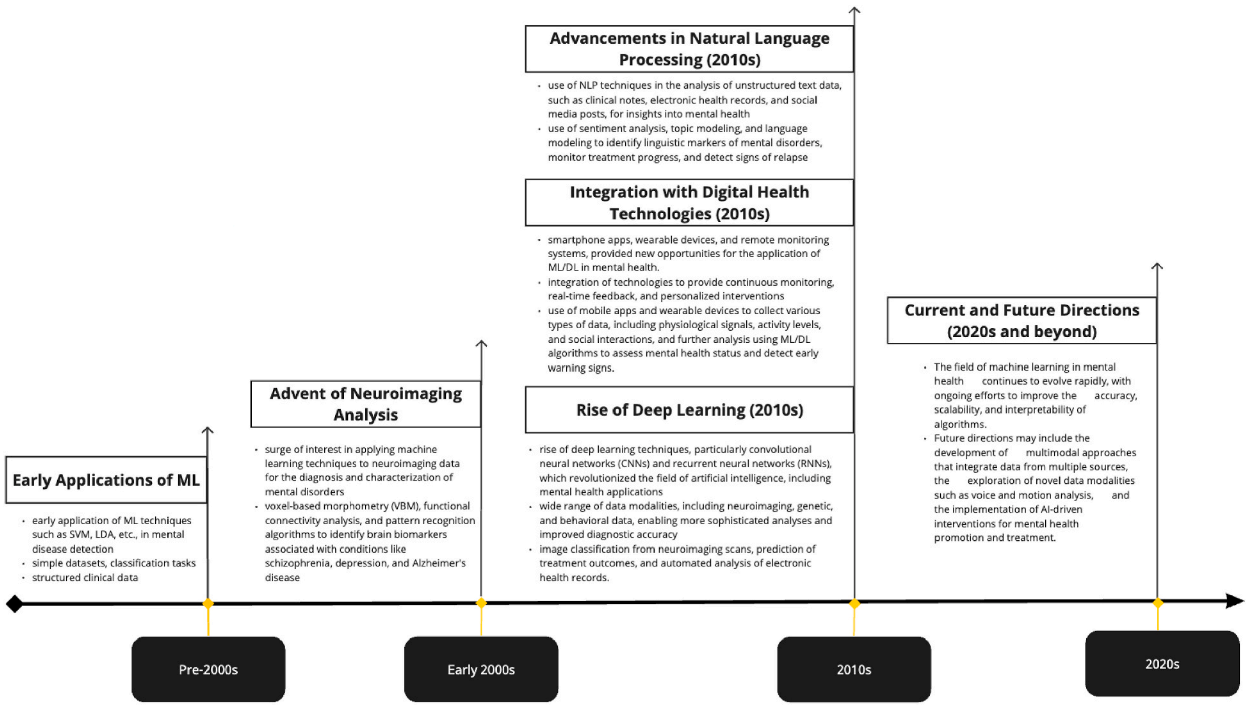

Fig. 1. Evolution of ML/DL applications in mental disorder diagnosis.

Advancements in natural language processing (NLP) techniques in the 2010s enabled the analysis of unstructured text data, such as clinical notes, electronic health records, and social media posts, for insights into mental health using sentiment analysis, topic modeling, and language modeling to identify linguistic markers of mental illness, monitor treatment progress, and detect signs of relapse [40,41,42]. ML and DL based approaches have several advantages over the traditional manual screening.

- ML and DL based approaches can process and learn from vast amount of data and can understand patterns from the data.
- With ML and DL, it is possible to use multiple modalities of data that can present better insights that can be helpful not only in diagnosing but also in monitoring of the conditions.
- These methods can be helpful in early diagnosis of mental disorders.
- ML-based assessment tools are trained on large amounts of data representing variations and therefore, is less prone to the subjective bias as present in the clinician-based assessments and can be useful in creating consistency across assessments.

Future directions point toward multimodal approaches that integrate data from multiple sources, the exploration of novel data modalities, and the implementation of explainable AI-driven interventions for mental health promotion and treatment [12,43–45]. The field of ML/DL in mental health is rapidly evolving with ongoing efforts to improve the accuracy, scalability, and interpretability of algorithms.

3. Materials and methods for the bibliometric study and review

3.1. Search strategy and data source

The potential keywords and phrases based on the main concepts identified from a preliminary review of the area and brainstorming among three researchers. The list was further improved by considering synonyms, related terms, acronyms, and variations in spelling or phrasing to ensure comprehensive coverage [46].

Following search string was used to retrieve the documents from Scopus database. The substring is divided into three parts, which combined with the binary operators OR and AND.

("Mental Disorder*" OR "Mental Disease*" OR "Mental Afflictions" OR "Major Depressive Disorder*" OR "Anxiety Disorder*" OR "Bipolar Disorder*" OR "Schizophrenia" OR "Obsessive Compulsive Disorder" OR "Post-Traumatic Stress Disorder" OR "PTSD" OR "ADHD" OR "Eating Disorder*" OR "Substance Use Disorders" OR "Borderline Personality Disorder")

AND.

("Diagnosis" OR "Detection" OR "Screening" OR "Classification" OR "Categori?ation") **AND.**

("Machine Learning" OR "Support Vector Machine*" OR "Decision Tree*" OR "XGB" OR "Supervised Learning" OR "Artificial Intelligence" OR "AI" OR "Deep Learning" OR "Neural Network*" OR "Artificial Neural Network*" OR "CNN" OR "LSTM")

Fig. 2 outlines the systematic process for identifying and screening literature items for bibliometric analysis and review.

The following inclusion criteria were used during searching for literature from the Scopus database.

- The time range is from January 1, 2012, to June 9, 2023.

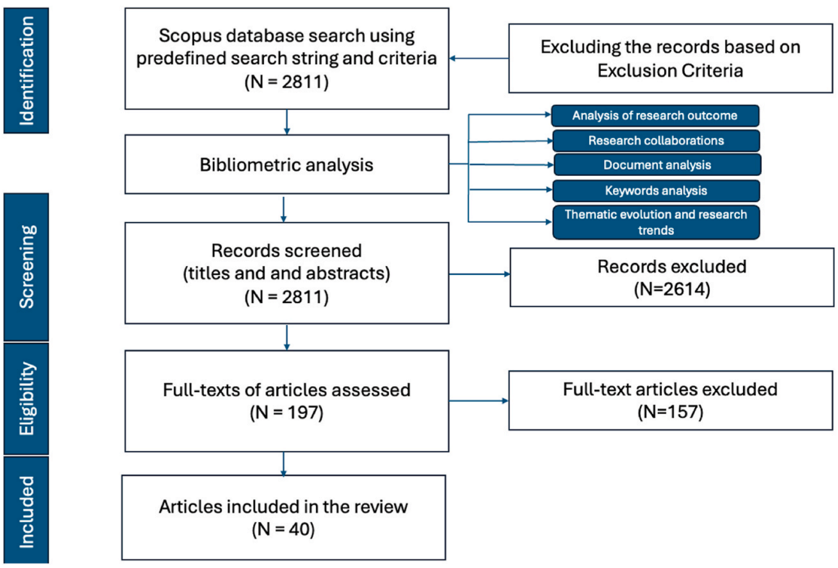

Fig. 2. Systematic process for bibliometric analysis and review.

- The language is English.
- The type of article is a journal article (research or review).

Furthermore, the following exclusion criteria were defined.

- Excluded those records that were out of the predefined range.
- Excluded records in languages other than English.
- Excluded conference papers, book chapters, books, notes, etc.

A total of 2811 records were retrieved for the bibliometric analysis that met the inclusion and exclusion criteria. A total of 2614 records were eliminated after reading titles and abstracts. Subsequently, a total of 197 articles were reviewed for full text by three independent experts. Finally, 40 research studies were selected for review.

3.2. Software and tools

For the data analysis, R Studio's (version 2023.03.1 + 446) was used. The 'bibliometrix' version 4.1.2 package that comes with 'biblioshiny' graphical user interface helped get the bibliometric analysis and visualizations of the data.

4. Results

4.1. Analysis of scientific production

Fig. 3 shows the annual scientific outcome of research papers from 2012 to June 2023. It is evident that since year 2017 there is an increasing trend in the annual publication outcome. There is an annual growth of 17.05 %. Year 2022 has the maximum outcome of 699 publications. In 2012, there were just 54 publications; that number rose to 699 in 2012. Over the course of a decade, the publication count has increased by 1194.44 %. The increasing prevalence of mental disorders in recent years (during and after the COVID-19 pandemic), as well as advancements in ML techniques, newer types of data modalities, and interdisciplinary research, all contribute to the growing number of research publications.

4.2. Analysis of publication sources

The Journal of Affective Disorders has published the maximum number of documents (n = 97**)** followed by Frontiers in Psychiatry (n = 91), and Plos One (n = 60). The top 10 journals along with number of publications have been shown in Table 1. Here, assessment of productivity of a journal has been done in terms of number of publications.

Number of publications can be a measure of the publication outcome of a source (journal), however, it may not be a direct measure of the productivity. It helps identify the relevant sources in a particular field. However, in order to establish the impact and relevance of a source, other factors, such as the citations received by these publications, can be helpful.

Among the ten journals in Table 1, seven are dedicated to mental health research, while the remaining three (Plos One, Scientific Reports, and IEEE Journal of Biomedical and Health Informatics) have an interdisciplinary focus. The growing volume of publications in these interdisciplinary journals suggests a heightened research interest in the field.

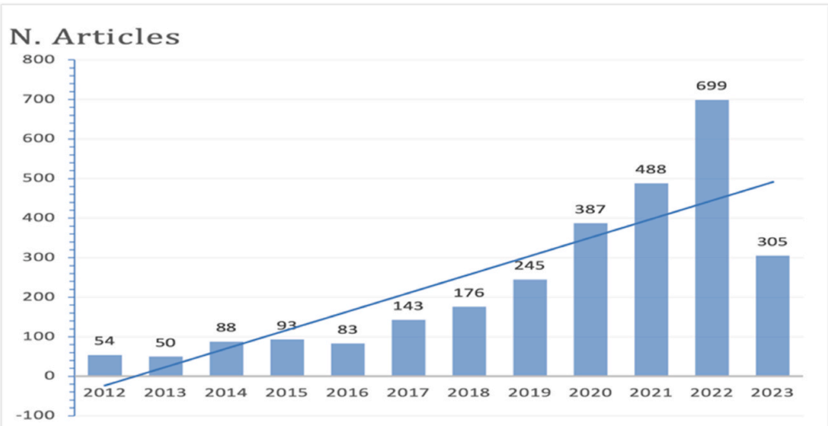

Fig. 3. Annual scientific production of publications.

Table 1
Most productive sourrces in terms of number of publications.

S.No	Sources	# Articles
1	JOURNAL OF AFFECTIVE DISORDERS	97
2	FRONTIERS IN PSYCHIATRY	91
3	PLOS ONE	60
4	SCIENTIFIC REPORTS	46
5	TRANSLATIONAL PSYCHIATRY	45
6	HUMAN BRAIN MAPPING	43
7	IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS	42
8	JOURNAL OF PSYCHIATRIC RESEARCH	40
9	SCHIZOPHRENIA RESEARCH	40
10	FRONTIERS IN NEUROSCIENCE	39

4.3. Authors' publication outcome and collaboration

Wang Y. has published the maximum number of documents (n = 64) and having a aricles fractionalized factor of approaximately 7.87. These details for top 10 researchers have been given in Table 2.

Lotka's law, based on a power-law distribution, describes the relationship between author productivity and the frequency of their publications [47]. It states that the number of authors who publish a single article is significantly higher than those who publish multiple articles. By analyzing the distribution of publications, Lotka's law allows for quantifying author productivity, and assessing the concentration or inequality within a field. Fig. 4 shows the frequency distribution plot of the author productivity, which shows that around 80 % of the authors have written less than 5 % of the documents.

The authors' collaboration is shown in Fig. 5. Collaboration among a total of 49 authors is presented. A total of nine clusters are formed using the "walktrap" clustering algorithm. The top author nodes from each of the clusters are selected and shown in Table 3. The author node "chen j" has the highest betweenness degree of centrality (≃83.07), followed by "wang y" (≃51.49), and "li m" (≃28.74). The most productive author is Wang Y, however, on collaboration metrics, Chen J. leads.

4.4. Most relevant affiliations and countries

West China Hospital of Sichuan University (n = 189) has the greatest number of publications as an affiliating institute of authors, closely followed by the University of California (n = 181). The top 10 most productive affiliations are shown in Fig. 6. Interestingly, Sichuan University appears in 110 more places (see Fig. 6). All 10 of the top 10 institutes come from China and the United States of America.

The prominence of institutions from China and the USA in the most productive affiliations underscore their leadership in academic and research endeavors in the field. Both countries benefit from generous funding mechanisms that support ambitious research projects and enable institutions to attract top talent and invest in state-of-the-art facilities. Moreover, the vast and diverse academic landscapes in China and the USA, comprising numerous universities, research institutes, and laboratories, foster collaboration and innovation across disciplines. International partnerships further enhance their global reach and impact, while government support and policies prioritize research excellence and incentivize publication output.

Furthermore, as far as the corresponding authors' affiliations are concerned, these two countries emerge at the top. The analysis of the corresponding author's countries reveals that China is the most productive country, both for multiple-country publications (MCP) and single-country publications (SCP) (Fig. 7). The USA and India follow China in the list of the top 19 countries.

Although there are more documents published from China, the documents published by US affiliations have received more citations. In an analysis of citations by the top 10 countries, the USA received a total of 11,697 citations; China received 7078; and Canada received 2071 citations. The Netherlands has the highest average article citations (25.6), while the USA remains in second place (22.5), as shown in Table 4.

Table 2
Most productive authors.

Authors	# Articles	Articles Fractionalized
WANG Y	64	7.87
LI Y	54	7.78
ZHANG J	54	8.80
ZHANG Y	51	6.52
CHEN J	47	5.37
LI X	43	6.05
LI H	42	6.79
WANG J	41	6.15
LIU Y	39	5.24
ZHANG X	33	4.29

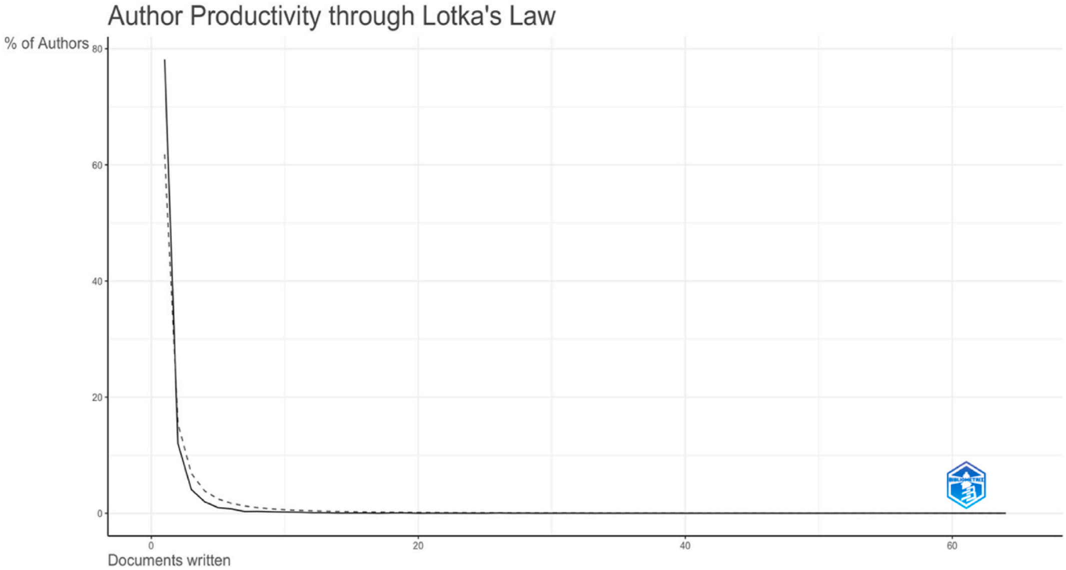

Fig. 4. Author productivity through Lotka's law.

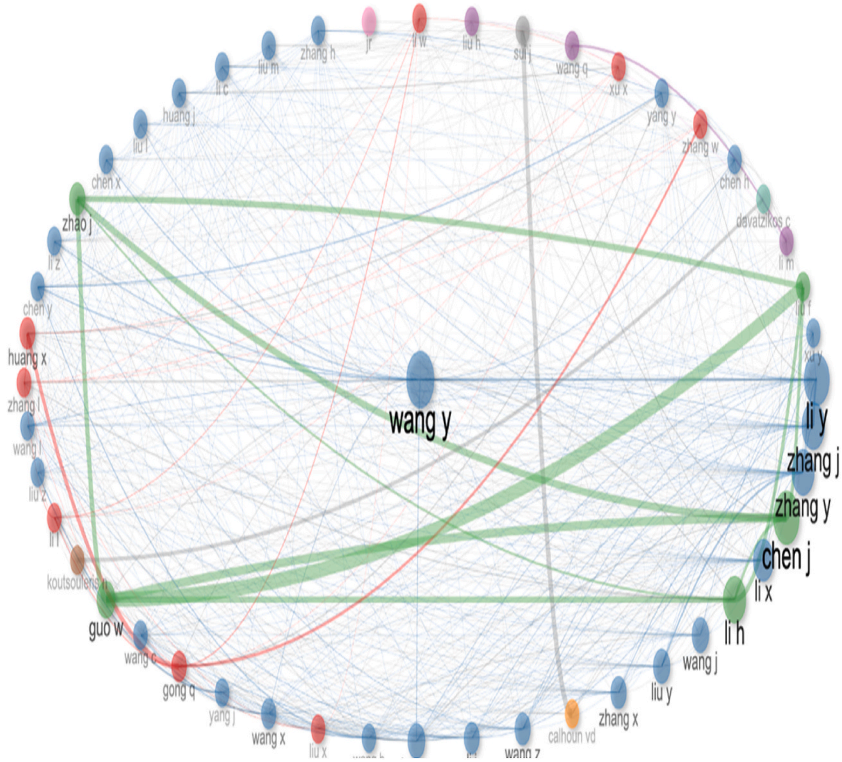

Fig. 5. Authors' collaboration map (type = star, cluster algorithm = walktrap).

4.5. Most cited documents

The top-cited document by Ref. [48], published in the NeuroImage journal of Elsevier, has a total citation count of 527 (see Table 5). With a focus on schizophrenia, and other MDs, this paper offers a thorough review of neuroimaging-based brain disorders diagnosis for single subject use-cases. It includes more than 200 reports in this field. The next top cited paper is by Ref. [49], having a citation count of 366, and describing a validation study for the applicability of DL for neuroimaging. In general, neuroimaging is the

Table 3
Cluster-wise top connecting author nodes based on betweenness.

Node	Cluster	Betweenness	Closeness	PageRank
chen j	3	83.07	0.0161	0.0425
wang y	2	51.49	0.0166	0.0404
li m	4	28.74	0.0121	0.0161
gong q	1	25.14	0.0129	0.0231
calhoun vd	5	24.65	0.0114	0.0140
davatzikos c	9	21.85	0.0105	0.0131
sui j	8	6.57	0.0123	0.0172
koutsouleris n	6	0.69	0.0076	0.0118
jr	7	0.00	0.0086	0.0043

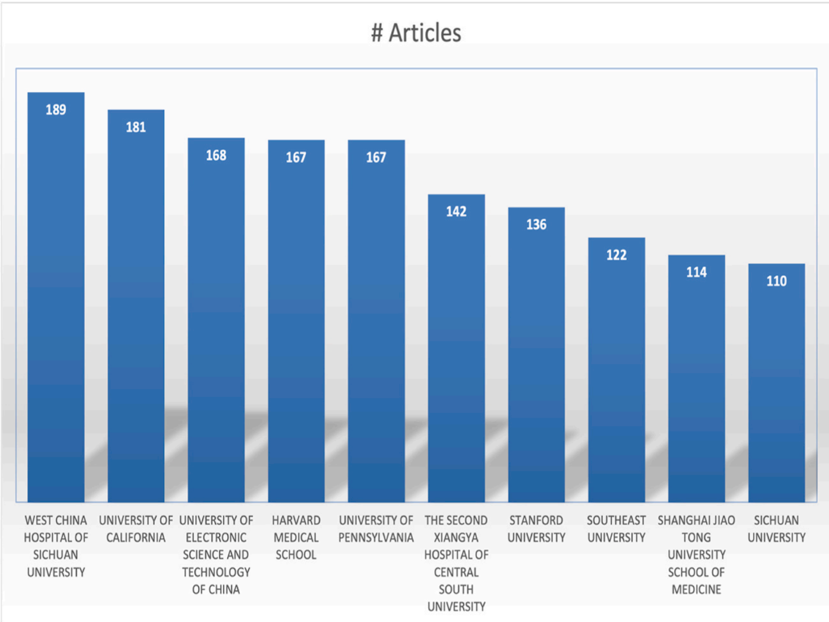

Fig. 6. Most productive affiliations.

area that has received more citations and interest of the researchers. Neuroimaging techniques, such as magnetic resonance imaging (MRI), functional magnetic resonance imaging (fMRI), electroencephalography (EEG), positron emission tomography (PET), diffusion tensor imaging (DTI), among others, visualize the structure and function of the brain and offer valuable insights for diagnosing various mental disorders [15,50]. Researchers have used them to detect various mental disorders such as schizophrenia, depressive disorders, bipolar disorder, and anxiety disorders [45,49,51–53].

4.6. Reference Publication Year Spectroscopy analysis

The idea of Reference Publication Year Spectroscopy (RPYS) was proposed by Leo Egghe, a Belgian mathematician and information scientist. Egghe introduced RPYS in his 2006 paper titled "Theory and practice of the g-index," published in the Journal of the American Society for Information Science and Technology. While the term "Reference Publication Year Spectroscopy" may not have been explicitly mentioned in Egghe's paper, the concept and methodology behind RPYS were described in his work. Since then, RPYS has been further developed and applied by various researchers in the field of bibliometrics and scientometrics.

The spectroscopy of references in the published research is shown in Fig. 8. The oldest reference dates to the year 1713. The work related to mental disorder diagnostic scales have received more citations. From the period of 1713–1960, the work describing Hamilton depression rating scale (HDRS) appears 62 times in the references, while the average for this period remains to be 1.3256.

4.7. Keywords analysis

From the keyword analysis presented in Fig. 9, it is evident that machine learning (n = 740) is the most frequently occurring word, followed by schizophrenia (n = 427), classification (n = 219), depression (depression, n = 200; major depressive disorder, n = 152), DL (n = 195). Therefore, depression and schizophrenia are the most studied afflictions as far as the application of ML and DL is

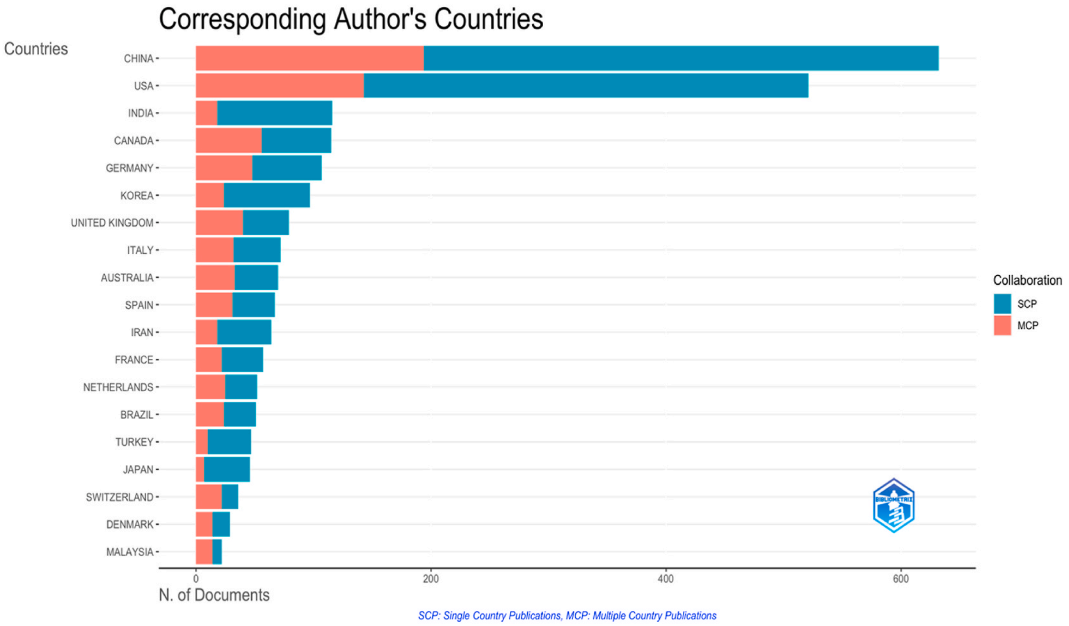

Fig. 7. Corresponding author's countries.

Table 4
Top 10 most cited countries.

Country	Total Citations	Average Article Citations
USA	11697	22.50
CHINA	7078	11.20
CANADA	2071	18.00
GERMANY	1716	16.00
UNITED KINGDOM	1693	21.40
KOREA	1506	15.50
NETHERLANDS	1330	**25.60**
INDIA	1281	11.00
ITALY	1047	14.50
SPAIN	906	13.50

Table 5
Top 10 most cited documents.

Paper Reference	Source	Total Citations	TC per Year	Normalized TC
[48]	NEUROIMAGE	527	75.28	14.22
[49]	FRONT NEUROSCI	366	36.60	7.23
[54]	NPJ SCHIZOPHR	344	38.22	7.64
[55]	CEREB CORTEX	334	33.40	6.59
[56]	PROC NATL ACAD SCI U S A	330	27.50	5.05
[57]	NEUROIMAGE	306	25.50	4.68
[58]	NAT MED	300	60.00	12.37
[59]	JAMA PSYCHIATRY	298	33.11	6.62
[60]	BRAIN STRUCT FUNCT	273	30.33	6.06
[61]	SCHIZOPHR BULL	252	21.00	3.85

concerned for mental disease detection.

The word co-occurrence network, represented in Fig. 10, shows that machine learning is correlated with several mental afflictions, including depression, schizophrenia, autism, anxiety, ADHD, obsessive-compulsive disorder, and PTSD. Support vector machines (SVM), decision trees, and random forests are the most popular ML algorithms. Furthermore, deep learning finds strong connections with neuroimaging, magnetic resonance imaging (MRI), fMRI, electroencephalogram (EEG), and bipolar disorder.

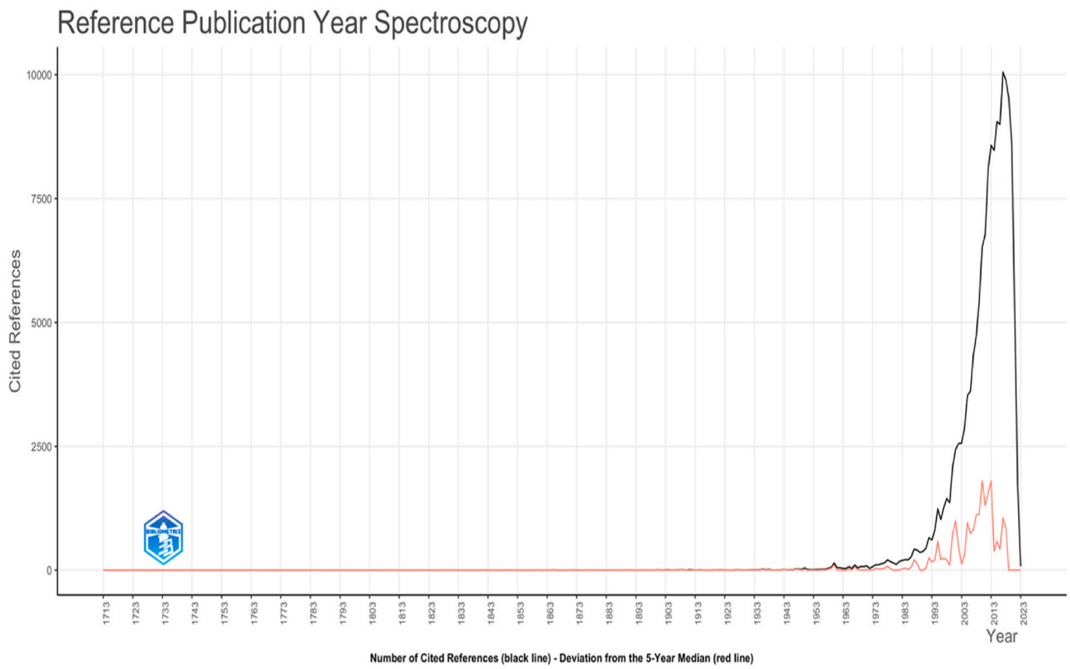

Fig. 8. Reference publication year spectroscopy.

Fig. 9. Word tree representation of the top 50 keyword occurrences.

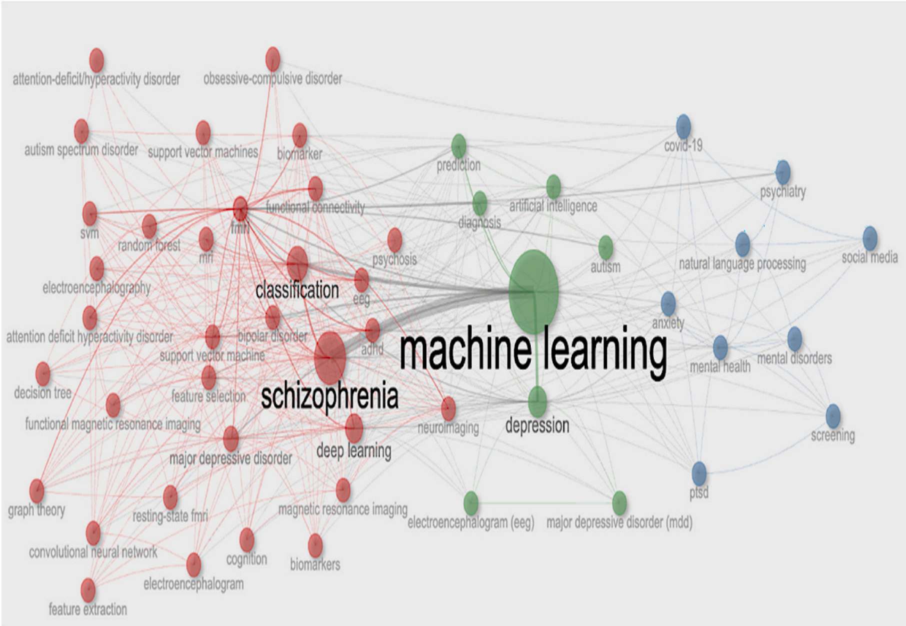

Fig. 10. Word co-occurrence network.

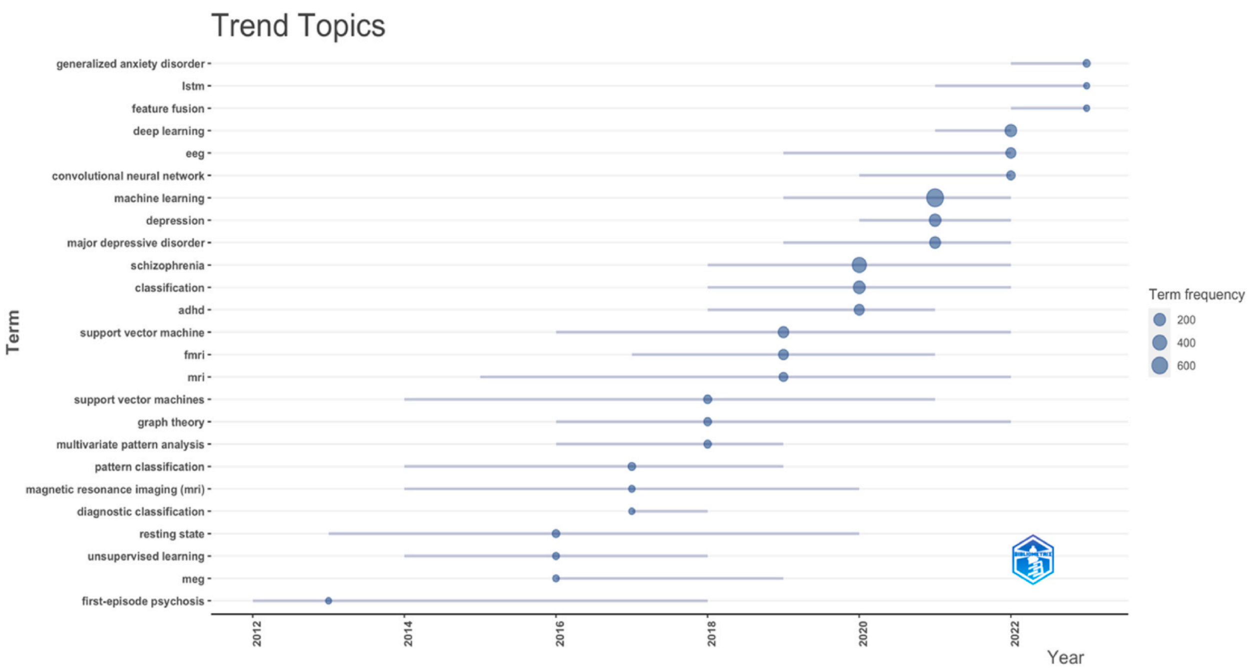

Fig. 11. Trend topics in the literature.

4.8. Research trend analysis and clustering

Fig. 11 shows the trend topics in the literature. The research in the area started around first-episode psychosis, magnetoencephalography (MEG), resting state, and unsupervised learning. On the other hand, long-short-term memory (LSTM), generalized anxiety disorder, feature fusion, deep learning, and convolutional neural networks are the modern-day trending topics in research.

Fig. 12 shows the various themes in the literature based on the keyword analysis. For generating this thematic map, the Walktrap clustering algorithm was used. The themes are divided into four quadrants, namely “emerging or declining themes”, “basic themes”, “niche themes”, and “motor themes”.

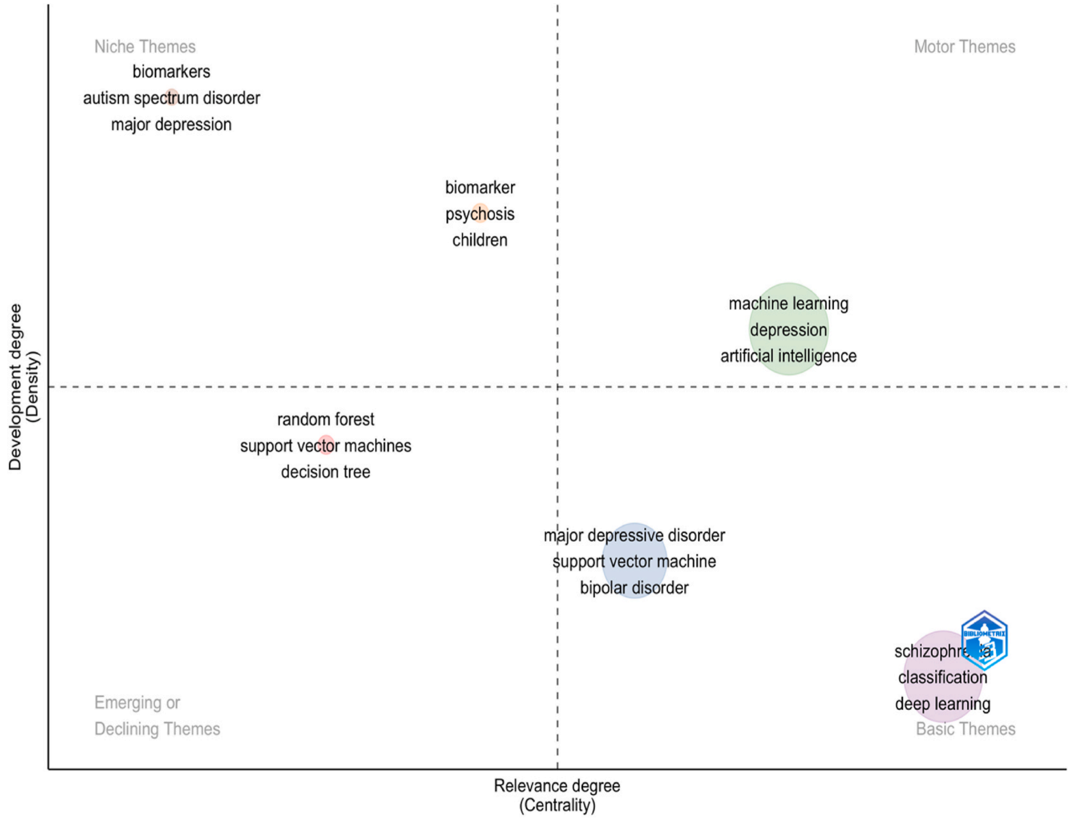

Fig. 12. Thematic mapping **under four categories.**

- *Basic Themes:* These are fundamental concepts that serve as the cornerstone within a specific domain or field, forming the essential building blocks for further exploration and development. Thematic areas like "schizophrenia," "major depressive disorders," "support vector machines," "bipolar disorder," and "classification" are foundational topics in the basic themes.
- *Emerging or Declining Themes:* These are trends or topics that are either gaining traction and becoming more popular over time or losing relevance and fading away from research interest. Under this group, "decision trees," "support vector machines," and "random forests" are included.
- *Niche Themes:* Niche themes are specialized topics that cater to a specific group of people, offering unique and focused content that may not have broad appeal but holds significant importance to its targeted audience. "Biomarkers," "autism spectrum disorder," "major depressive depression," "psychosis," and "children" are the constituent elements of the niche themes.
- *Motor Themes:* It refers to recurring elements or ideas of symbolic significance that contribute to the central themes of literature. "Machine learning," "depression," and "artificial intelligence" are the topics of motor themes.

The thematic evolution based on various keywords has been shown in Fig. 13. It has been divided into two-time spans 2012–2021 and 2022-23. The latter represents the more recent work in the field.

5. Mental disorders, ML methods, data modalities and performance analysis of 40 most relevant research articles

Contrary to ML/DL based methods, there exist traditional approaches that primarily rely on responses received to certain questions and investigation done by the clinicians [4,62]. However, this approach has some serious limitations. Firstly, given the shortage of trained clinicians and longer times in evaluating the patients manually, it becomes ineffective, and secondly, questionnaire-based scales provide limited knowledge in understanding the issue [63,64].

ML has proven to be efficient in general disease diagnosis, prognosis, and therapy suggestions [10,65–67]. The progress in the field of mental disease diagnostics has been steadily growing and ML models can be trained by using a variety of data [44,68,69]. However, the choice of the techniques depends on many factors, including volume, type of data, nature of the task, etc. The selection of datasets and ML algorithms depends on the availability of data and the specific characteristics of each mental disorder.

For the diagnosis of depression, datasets can include clinical assessments, self-report questionnaires, EEG and fMRI data, and even social media activity data [15,70,71]. ML techniques, including support vector machines (SVM), k-nearest neighbors, random forests, neural networks, etc., are utilized for depressive disorder detection. Similarly, anxiety can be diagnosed using psychological

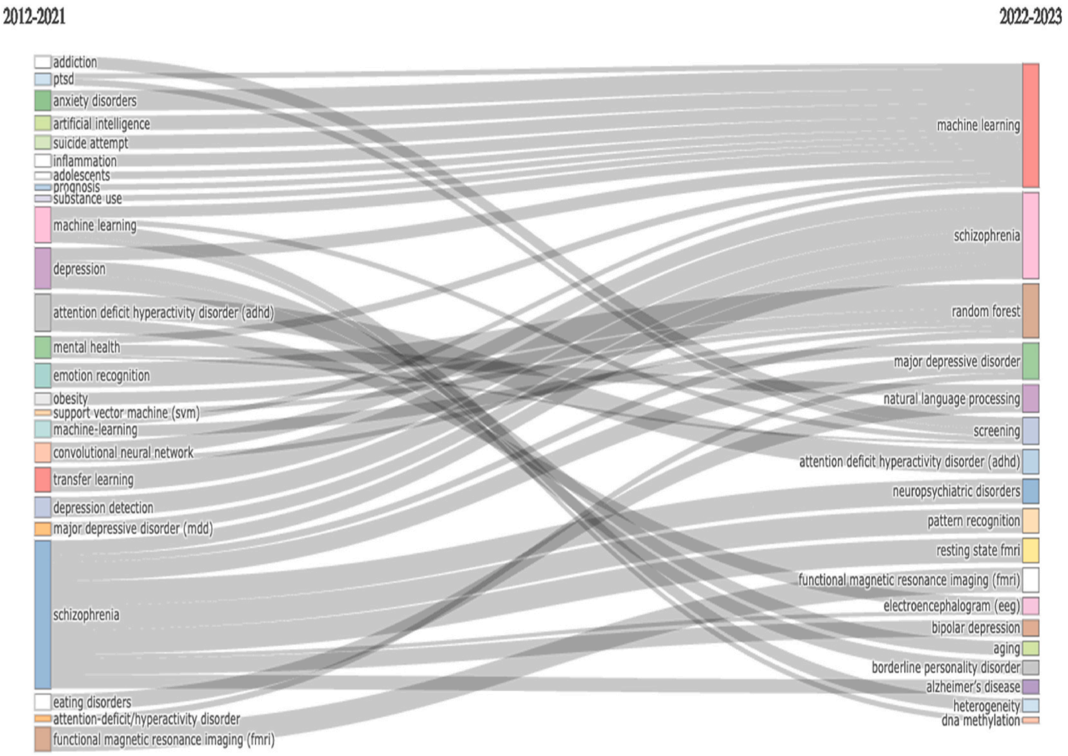

Fig. 13. Thematic evolution of concepts in the field.

assessments, physiological data like heart rate and cortisol levels, textual data from therapy sessions, and mobile sensor data [60,72,73]. ML algorithms like decision trees, K-nearest neighbors (KNN), naive Bayes, and gradient boosting machines (GBM) can be employed for anxiety diagnosis [72,74]. For schizophrenia, structural and functional brain MRI, eye-tracking data, and EEG are used as datasets, while ML methods such as convolutional neural networks (CNN), Gaussian mixture models (GMM), autoencoders, and recursive neural networks (RNN) aid in diagnosis [75,76].

In order to complete a comprehensive review of state-of-the-art research in the area of application of ML for MD diagnosis, a total of 40 research articles were finally selected. The selection was made keeping in mind the relevance, recency, and scope of the work by three independent experts. The cumulative sum of responses (1 for inclusion and 0 for exclusion) was chosen to make the final decision. The shortlisted articles were divided into seven classes based on the disease they represent, as shown in the Appendix Table B. The table continues to cover depressive disorders, anxiety disorders, schizophrenia, bipolar disorder, autism spectrum disorder (ASD), attention deficit hyperactivity disorder (ADHD), and obsessive-compulsive disorder (OCD). For each of the MDs, datasets, ML algorithms, performance evaluations, and key contributions have been provided.

Table 6 describes the different modalities of data in the mental disease diagnosis across the seven diseases. EEG is the most common modality of data that has been used for diagnosis for all the diseases. However, it is widely used in diagnosing schizophrenia, depressive disorders, bipolar disorder, and ASD. Furthermore, functional and static MRI is the next most widely used data modality, which has been used in diagnosing ADHD, ASD, and schizophrenia.

Fig. 14 shows the use of ML methods (including deep learning) in MD diagnosis. It is evident from the data that deep learning methods dominate the pie distribution. Neural networks and their variants, including CNN, autoencoders, PNN, and transformers, have been found in use in 67 % of the studies. As far as the usage of traditional ML methods is considered, SVM (15 %) is the most preferred method, followed by XGB (8 %), and logistic regression (5 %).

6. Discussion

The application of ML to mental disorder diagnosis is being extensively used. The scientific research outcome in the field has grown at an annual rate of 17.05 percent. The Journal of Affective Disorders has published the largest number of documents (n = 97). Wang Y. has published the largest number of documents (n = 64). Lotka's law, which claims that most publications on a topic come from a minority of the authors, almost fits. The most productive author is Wang Y; nevertheless, on collaborative metrics, Chen J. leads. West China Hospital of Sichuan University has the biggest number of publications as an affiliating institute of authors, closely followed by the University of California. All 10 of the top 10 institutes come from China and the United States of America. Although there are more documents published from China, the documents published by US affiliations have received more citations. The top-cited document by Ref. [48], published in the NeuroImage journal of Elsevier, has a total citation count of 527 and is a review paper. Depression and

Table 6
Disease-wise modalities of data for MDs diagnosis.

Mental Disorder	Data Modality	Count
ADHD		
	EEG	3
	fMRI	2
	Clinical intelligent test data	1
ASD		
	EEG	2
	Clinical physiology features	1
	Motor Developmental Data	1
	fMRI	1
Anxiety Disorders		
	EEG	1
	Heart Rate Variability Data	1
	Speech Transcripts Data	1
	fMRI	1
Bipolar Disorder		
	EEG	3
	Exomes data.	1
	Pathological data	1
Depressive Disorders		
	EEG	3
	Audio	2
	Electrodermal data	1
	Emotional health data	1
	Neuroimaging	1
	Smart phone data	1
	fNIRS	1
OCD		
	Behavioral data	1
	EEG	1
	Sociodemographic and clinical data	1
Schizophrenia		
	EEG	4
	The scanned fingerprints data	1
	fMRI	1
	sMRI	1

schizophrenia are the most studied afflictions as far as the application of ML and DL is concerned for mental disease detection. The word co-occurrence network analysis shows that ML is correlated with several mental afflictions, including depression, schizophrenia, autism, anxiety, ADHD, obsessive-compulsive disorder, and PTSD. Support vector machines (SVM), decision trees, and random forests are the most popular ML algorithms. Furthermore, deep learning finds strong connections with neuroimaging, magnetic resonance imaging (MRI), fMRI, electroencephalogram (EEG), and bipolar disorder. Deep learning, long-short-term memory (LSTM), generalized anxiety disorder, feature fusion, and convolutional neural networks are the modern-day trending topics in research.

A review on using ICT tools for stress, anxiety, depression (SAD) in students has been presented in Ref. [73]; wherein different modalities of data, such as symptomatic questionnaires, audio, video, and physiological sensor data, and the suitability of ML approaches were discussed. Logistic regression, random forest, SVMs, and ANNs work well with numeric data, while random forests work well in the case of genomic data, with accuracy varying from 60 to 100 % [77]. Smart mental health assessment tools can be deployed in various settings, including primary care clinics and online platforms, making it easier for individuals to seek help anonymously and without fear of stigma [78,79]. This increased accessibility can encourage more people to seek early intervention and support [80].

In a review of the application of ML in clinical practice for outcome prediction, it was found that 91 % of studies met just more than 50 % of the criteria for the TRIPOD checklist (for prediction model development), and no study was complying with the PROBAST checklist (for risk of bias assessment) [81]. Therefore, there is a strong need to make ML model development transparent, reliable, bias-free, and more in compliance with the standards. Better transparency and interpretability of ML models will make them more acceptable as explainable AI becomes more widespread. The use of automated screening methods for mental health will increasingly rely on ML in the near future. Furthermore, the application of AI and ML can help tailor treatment plans, keeping in mind a patient's individual factors such as genetics, lifestyle, and response to previous treatments, which can lead to optimized treatment efficacy and reduce the trial-and-error in medication selection.

6.1. Future research directions and implications

Future research directions in ML-based MDs diagnosis should aim to address the complex challenges associated with data integration, personalization, interpretability, generalizability, ethics, and implementation, ultimately leading to improved diagnosis, treatment, and outcomes for individuals with mental health conditions.

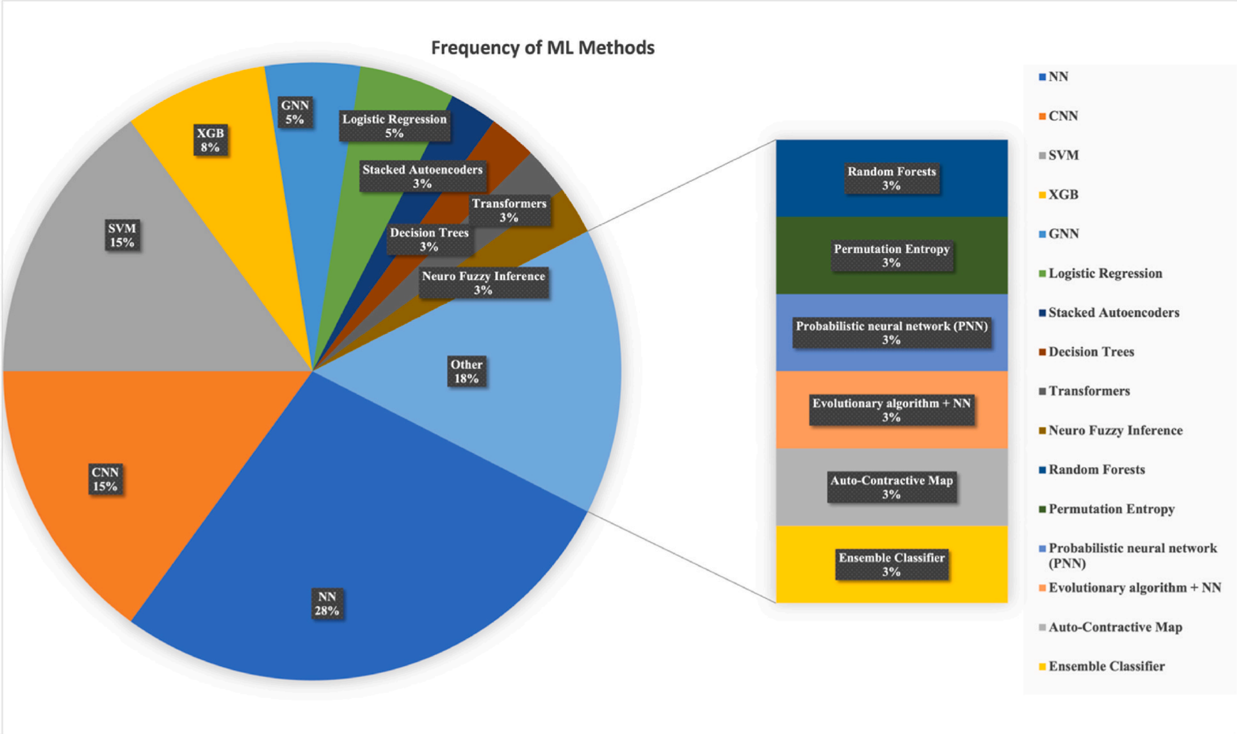

Fig. 14. Pie distribution of different ML methods used in MD diagnostics.

- **Collaboration and Interdisciplinary Research**: Collaborations between computer scientists, clinicians, psychologists, neuroscientists, and other stakeholders are essential for advancing research in ML-based MDs diagnosis. Future research could encourage interdisciplinary collaborations to leverage complementary expertise and foster innovation in this rapidly advancing field.
- **Multimodal Data Fusion:** Multimodal approaches have been effective in accurate and reliable diagnosis of MDs [82,83]. Future approaches will rely more on a combination and fusion of different modalities of data such as electronic health records, neuroimaging, genetic data, and behavioral data.
- **Personalized Diagnostics and Treatments**: ML algorithms will find a way to provide individualized diagnostics and treatment suggestions, considering the unique biological, psychological, and social factors of individuals [30,84]. It will lead to more effective and targeted interventions.
- **Longitudinal Analysis and Disease Prognosis**: Investigating the temporal patterns and trajectories of mental disorders over time can help understand disease progression and treatment response. ML techniques utilizing temporal aspects of data can predict and forecast future outcomes.
- **Ethical and Privacy Considerations**: Addressing ethical and privacy concerns regarding data collection, storage, and usage becomes imperative in ML-based MDs diagnosis. Future research should focus on developing privacy-preserving ML techniques and ethical guidelines to ensure responsible deployment of these technologies in clinical practice.

Validating ML-based diagnostic models in real-world clinical settings is crucial for assessing their effectiveness and utility. Future research should prioritize large-scale clinical trials and implementation studies to evaluate the impact of ML-based MDs diagnostic tools on patient outcomes, clinician workflow, and healthcare delivery.

Developing ML models that are interpretable and explainable is crucial for gaining insights into the underlying mechanisms of mental disorders [43]. Future research should focus on enhancing the transparency and interpretability of ML models to facilitate trust and understanding among clinicians and patients.

7. Limitations and scope of the current study

The current study is based on only the Scopus database and considers only journal articles. These considerations may have their own advantages and disadvantages. However, to ensure the quality of the articles used for an accurate analysis, only journal articles were included. Furthermore, Scopus is one of the largest research databases and takes qualifies further quality checks.

8. Conclusion

Due to the deep interest of researchers in the area of ML-based MDs diagnosis, the number of research publications in the field has been tremendously increasing. However, a bibliometric analysis and review of the literature was missing. The objective of this paper was to fill this gap. Here, we analyze the meta data of 2811 journal articles from the Scopus database published in the last 10.5 years (January 2010–June 2023). Our analysis suggests that the literature grew at an annual research growth of 17.05 %. The Journal of Affective Disorders published the most documents (n = 97), led by author Wang Y. (n = 64). Lotka's law is observed, with a minority of authors contributing the most publications. The West China Hospital of Sichuan University and the University of California are the top affiliated institutes. China and the US dominate the top 10 institutes. While China has more publications, US-affiliated papers receive more citations. Depression and schizophrenia are the primary focuses of ML and DL for mental disease detection. Co-occurrence network analysis links ML to depression, schizophrenia, autism, anxiety, ADHD, obsessive-compulsive disorder, and PTSD. Support vector machines (SVM), decision trees, and random forests are popular algorithms. Deep learning is associated with neuroimaging techniques (MRI, fMRI, and EEG) and bipolar disorder. Current research trends include deep learning, LSTM, generalized anxiety disorder, feature fusion, and convolutional neural networks. Though the bibliometric analysis and the review of the literature are based on limited data, they will pave the way for further exploration as more research is done in the future.

Data availability statement

The data used for bibliometric analysis and review are available with authors and may be provided on a reasonable request to the corresponding author.

Role of funding

The work did not receive any funding.

CRediT authorship contribution statement

Chandra Mani Sharma: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **Vijayaraghavan M. Chariar:** Writing – review & editing, Supervision, Project administration, Investigation.

Declaration of competing interest

We declare that there is no conflict of interest. All authors have read the manuscript and agree on its publication in the journal.

Acknowledgement

None.

Appendix

Table ADescription of the Bibliometric Dataset

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2012:2023
Sources (Journals, Books, etc)	815
Documents	2811
Annual Growth Rate %	17.05
Document Average Age	3.12
Average citations per doc	16.57
References	138186
DOCUMENT CONTENTS	
Keywords Plus (ID)	12741
Author's Keywords (DE)	5546
AUTHORS	
Authors	13288
Authors of single-authored docs	60
AUTHORS COLLABORATION	
Single-authored docs	65
Co-Authors per Doc	7.49
International co-authorships %	34.76

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(*continued*)

Description	Results
DOCUMENT TYPES	
article	2811

Appendix: Table B
State-of-the-art Techniques for Mental Disease Diagnosis using Machine Learning

Mental Disorder	Study	Dataset Used	ML Algorithm Used	Highest Performance Reported	Contributions
Depressive Disorders	[85]	Electrodermal data of 38 university students	Stacked Autoencoders + DNN	Accuracy: 92 %–94 %	Classification into five classes (1 normal + 4 depression severity classes)
	[45]	Neuroimaging Data of 533 subjects	Graph convolutional network with feature fusion	Accuracy: 66 %	Combined functional and structural MRI data for depression detection in a four-stage AMNI framework.
	[86]	fNIRS data of 32 subjects	Neural networks	Accuracy: 99.94 %	The findings propose using fNIRS measurements of the PFC for a better diagnosis of MDD.
	[87]	EEG Data of 80 subjects (equally distributed into depressive and HC classes)	Convolutional neural networks (EEGNet)	Accuracy: 94.85 %	Resting-state EEG data from 80 were collected using three electrodes (FP1, FZ, FP2). High accuracy with just three channels.
	[88]	Emotional health data of 1047 volunteers.	SVM	Accuracy: 90%–92 %	A framework to develop AI-enabled mobile phone Apps that use emotional health data to make predictions. Also, recommending coping strategies based on level of depression.
	[70]	EEG Data	SparNet (a CNN architecture)	Classification accuracy of 94.37 %	This research focuses on "EEG Space-Frequency Feature Learning" to discriminate depression. The study aims to develop methods to extract features from EEG signals in both spatial and frequency domains for accurate depression detection.
	[89]	Smartphone data user physical activity patterns	Support Vector Machines	Accuracy: 87.20 %.	Severity of depression in severe, moderate, absence classes using physical activity data captured using a smartphone.
	[14]	Audio features	Graph Convolutional Neural Network	Classification and severity scoring, accuracy of 92%–98 %.	Depression detection from audio data. However, the model is able to detect depression only when test and train data included the same subjects.
	[90]	Classification using Theta asymmetry and Alpha power of EEG Data	Support Vector Machines	Accuracy: 88.33 %	Alpha power and theta asymmetry combination can be a good discriminator for MDD detection.
	[91]	Voice data having 1479 samples	Decision Tree	Accuracy: 83.40 %	The model utilizes voice data to detect potential signs of depression.
Anxiety Disorders	[92]	Heart Rate Variability Data of 161 patients	L1 Regularized Logistic Regression	Accuracy 78.40 %.	Discriminates panic disorder from anxiety disorders
	[60]	fMRI Data of 40 patients	SVM	Accuracy 82.50	Detection of social anxiety disorder.
	[93]	DEAP and SEED Datasets	Trace and Forage optimization Optimized ANN (TF-ANN) Classifier	Accuracy: 96.67 %	Anxiety disorder is detected by evaluating the frequency bands present in EEG signals and performing feature extraction.
	[74]	Impromptu Speech Transcripts of 2000 persons	Transformer-based Neural Networks	AUCROC: 0.64	Involving 2000 participants, the study used a transformer-

(*continued on next page*)

Appendix: Table B (*continued*)

Mental Disorder	Study	Dataset Used	ML Algorithm Used	Highest Performance Reported	Contributions
					based neural network to predict anxiety levels based on impromptu speech and GAD-7 scores. The model surpassed a baseline LIWC-based logistic regression in performance. Specific words, like "I," influenced predictions differently depending on the context, with silent pauses also playing a role.
Schizophrenia	[76]	sMRI Data of 146 subjects	Neural network model for Classification and Wilcoxon method for feature selection gives best performance when white and grey matter combination is used for computation.	Classification accuracy: 83.98 %	In abstract they mention SVM as the top performer, while results show that NN is the best algorithm for Schizophrenia classification.
	[94]	EEG data of 140 subjects belonging to three classes, namely, First Episode Schizophrenia, Chronic Schizophrenia and Healthy Controls	Graph Neural Network	Classification accuracy: 84.17 %	GNN-based model classifies different types of schizophrenia from EEG data.
	[95]	The scanned fingerprints data of total 1456 subjects falling into two classes, patients and controls.	CNN model	Accuracy: 70 %	Fingerprints can serve as an effective method for early psychosis diagnosis. ML model uses model use images from the left thumb, index and middle fingers.
	[96]	6250 EEG data samples of patient and control volunteers (14 + 14 subjects) using 19-channel device.	SVM with RBF Kernel	Accuracy: 92.91 %	Feature selection from EEG data using *t*-test and classification using SVM for schizophrenia detection.
	[97]	Resting-state EEG data of 14 schizophrenia and 14 HCs.	Adaptive neuro-fuzzy inference system (ANFIS).	Accuracy: 100 %	Study found that for MDD and HC classification, alpha (O1), theta and delta (FZ and F8), and gamma (FP1) provide the most discriminatory information.
	[98]	The fMRI and grey matter volume (GMV) data consist of three classes, namely, deficit schizophrenic patients, nondeficit schizophrenic patients, and HCs (16, 31, and 38 subjects, respectively).	XGBOOST with Fusion Data	Accuracy: 73.88 %	Multiclass schizophrenia detection using fusion data consisting of fMRI data, GMV, and the amplitude of low-frequency fluctuations (ALFF)
	[99]	The EEG dataset of a total of 28 subjects equally distributed into schizophrenia and HC classes.	Random Forests	AUC Score: 0.99	Signals from the occipital region are significant in diagnosing the disease. The beta and theta frequency bands provide more discriminatory information as compared to the other frequency bands.
Bipolar Disorder	[100]	EEG dataset collected from 58 unipolar and 31 bipolar subjects.	PSO-ANN (Particle Swarm Optimized Artificial Neural Nets)	Accuracy: 89.89 %	PSO-based feature selection reveals that the features from alpha and theta frequency bands can be used to discriminate the unipolar and bipolar subjects' EEG data.
	[101]	Pathological data collected from 2470 hospitalized patients with bipolar disorder (n = 1333) or major depressive disorder (n = 1137). The data consisted of 8 biochemical attributes for male	Multiple Logistic Regression (MLR)	Accuracies: 76.90 % for males and 79.50 % in females.	Separate classification models for gender-specific (separate for male and female subjects) disease detection.

(*continued on next page*)

Appendix: Table B (*continued*)

Mental Disorder	Study	Dataset Used	ML Algorithm Used	Highest Performance Reported	Contributions
		subjects, while 12 for female subjects.			
	[102]	Bipolar exomes data containing 1000 samples.	DeepBipolar (a CNN Model)	Accuracy: 65 %	Utilization of genotype information and convolutional neural networks to make a prediction about the bipolar phenotype. The technique won a winner in a bipolar prediction challenge (the CAGI-4), demonstrating its effectiveness without requiring manual feature engineering.
	[103]	EEG Data	XGBOOST	Accuracy: 94 %	Detection of bipolar disorder from EEG data using XGB classifier.
	[104]	Spatiotemporal EEG data of 101 MDD patients, 82 bipolar disorder patients, and 81 HCs	CNN + Inception Time Network	Accuracy: 96.88 %	Study reveals that the learned features from spatiotemporal EEG daat are symmetrical to the neurobiological studies.
Attention-Deficit/ Hyperactivity Disorder (ADHD)	[105]	EEG data 10 children aged between 7 and 12 with equal distribution in ADHD and healthy control classes.	Permutation Entropy	Accuracy: 99.82 %	A variety of entropy measure including log, fuzzy, permutation, Shannon, and SURE entropies were evaluated for the detection of ADHD. Permutation entropy was the most effective and Shannon was the least effective measure in ADHD detection.
	[106]	EEG data of 47 ADHD and 50 HCs	Neural Dynamic Classifier	The top classification accuracies achieved for eyes-open, eyes-closed and CPT conditions were, 93.3 %, 90 %, and 100 %, respectively.	The work focused on utilizing the phase space reconstruction (PSR) of brain signals in order to make further classification.
	[107]	EEG data of 61 ADHD and 60 normal children.	6D CNN Model	Accuracy of 98.85 % for epoch-based classification. Accuracy of 99.17 % for subject-based classification.	13021 epochs used for model training and evaluation with connectivity measures wavelet coherence and synchronization likelihood.
	[108]	ADHD-200 resting state fMRI dataset	Neural Nets with ACO optimization.	Accuracy: 86 %	Comparative analysis shows that their approach is better at detecting ADHD than the phenotypic detection methods.
	[109]	Clinical intelligent test data based on SNAP-IV and CPT of ADHD-I, ADHD-C, and HC subjects.	Neural Nets	Accuracy: 77–86 %	Multiclass classification of child subjects into three categories using a neural network classifier
	[110]	fMRI Data of ADHD and HC subjects.	Fully connected cascade artificial neural network (FCC-ANN) architecture.	Accuracy of 90 % between ADHD and HC classification. Accuracy of 95 % between ADHD subtypes.	Most discriminative features reveal the pathophysiology of ADHD. For ADHD, it shows a diminished and altered connectivity involving the left orbitofrontal cortex and cerebellar regions.
Autism Spectrum Disorder (ASD)	[111]	EEG data converted into higher-order spectra (HOS) 2-D images.	Probabilistic neural network (PNN) classifier	Accuracy: 98.70 %	A condensed set of just five features, selected using student's t-test.
	[112]	Multi-site resting state fMRI data.	ANN	Accuracy on harmonized data: 71.35 %	The proposed CombBat techniques for harmonization of multi-site fMRI data can improves the performance of various ML methods, when compared with non-harmonized data.

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Appendix: Table B (*continued*)

Mental Disorder	Study	Dataset Used	ML Algorithm Used	Highest Performance Reported	Contributions
	[113]	Data of 2004 children having three neurodevelopmental disorders, including ASD, developmental language disorder (DLD), and global developmental delay (GDD).	XGB Classifier	Accuracy: 78.30 %	The data includes 14 features, which are used to train models for three-class classification. The study suggests information integration from multiple instruments to better understand the role of several behavioural and developmental characteristics.
	[114]	EEG data from two channels C3 and C4	Evolutionary algorithm and neural networks.	Accuracy: 100 %	The study proposes a new evolutionary approach (Gen-D) that is used in combination with a backpropagation neural network for classification.
	[115]	Data of 32 male children with ASD tested on Peabody Developmental Motor Scale-Second Edition.	ANN-based Auto-Contractive Map (Auto-CM) unsupervised analysis	–	Preschoolers with ASD often have poor motor skills, associated with high levels of recurring behavioral traits and low-level of expressive language.
Obsessive-Compulsive Disorder (OCD)	[116]	Data of 600 subjects belonging to the OCD and HC classes.	ANN	Accuracy: 98.2 %	Feature importance mapping revealed that contamination and cleaning is the most contributing factor in the determination of the OCD.
	[117]	Quantitative EEG data of 79 subjects into trichotillomania and OCD classes.	SVM	Accuracy: 81.04 % AUC Score: 0.816	Cordance (relative and absolute power of EEG spectra) can be used for c distinguishing the trichotillomania and OCD classes.
	[19]	Sociodemographic and clinical data of 151 OCD patients having finished fluvoxamine pharmacotherapy, divided into two classes – responder and non-reponder.	Ensemble Classifiers	Accuracy: 86 %	The highly influential predictors of resistance to fluvoxamine pharmacotherapy in OCD patients happen to be 'sexual and contamination obsessions', along with higher Y-BOCS (Yale-Brown Obsessive Compulsive Scale) obsessive scores.

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