Electroencephalogram (EEG) for Brain Disease Detection: A Bibliometric Analysis on 2013-2023 Research in the Scopus Database

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Abstract. The diversity of brain disease can be attributed to the complexity of the nervous system. External,genetic, and epigenetic factors such as physical trauma, illness, and environmental factors can cause and worsen brain disease. The advancement of technology has led many to seek a lifestyle that is both health-conscious and easy. Biomedical research and treatment use several signals, including electroencephalograms. EEG captures spontaneous electrical activity in the cerebral cortex and can detect, monitor, and help brain disease patients. This study employs the Scopus database to conduct a bibliometric analysis of the EEG research for brain disease detection. The data was evaluated using the RStudio and VOSviewer applications. One hundred ninety-three papers from 2013 to 2023 were included in the final bibliometric dataset. China is known as the most impactful country, and Harvard Medical School is well recognized as a highly productive institution with significant global contributions. Wang J is recognized as the most prolific author.The article authored by Oh et al. in 2020 holds substantial influence in the field. The most frequently appearing keywords were electroencephalogram (173 occurrences with a link strengthof 4740). These results are performed to provide a broad understanding of EEG research for braindisease detection.

Keywords: EEG, Brain, Disease, Bibliometric, Research, Database.

1 Introduction

The brain, with its 100 billion neurons connected by over 100 trillion synapses, is central to all cognitive and physiological processes, including movement, perception, and breathing [1]. Understanding the complex neuronal mechanisms behind these functions is crucial for researchers, especially as various neurological and mental illnesses affect

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both the central and peripheral nervous systems [2,3,4]. Such diseases are influenced by multiple factors like trauma, genetics, and the environment, with well-known conditions including multiple sclerosis (MS) [7], Alzheimer's disease (AD) [8], Parkinson's disease (PD) [9], cerebral palsy [10], autism spectrum disorder (ASD) [11,12], amyotrophic lateral sclerosis (ALS) [13], myasthenia gravis (MG) [14], traumatic brain injury [15], and epileptic seizures [16,17,18].

The rapid technological progress has heightened interest in health monitoring through biological signals like ECG, EEG, and others, with EEG being particularly valuable for its insights into brain activity [19,20,21]. This study uses a bibliometric approach to analyze scientific literature on EEG from 2013 to 2023, as no such comprehensive analysis exists in the Scopus database. The goal of bibliometric approach is to map out and evaluate the complex body of knowledge on EEG, assessing its use in understanding and treating brain disorders [22,23,24,25,26].

Moreover, it is imperative to comprehensively evaluate the study's intrinsic merit, thoroughly examine the primary areas of research, and anticipate the future direction of subsequent investigations [27]. So far, no bibliometric analysis has been undertaken on the electroencephalogram (EEG) from 2013 to 2023, as documented in the Scopus database. This study conducts a thorough bibliometric analysis to examine the complex conceptual framework of the subject. The analysis employs a retrospective research approach, focusing on publication trends, organizations, sources, papers, keyword co-occurrence networks, and informative overlays. Our review aimed to gain a comprehensive understanding of the application of electroencephalograms in detecting and treating brain disorders.

2 Materials and Methods

2.1 Methodology and Information Retrieval Approach

This research utilized data from the Scopus database, specifically selecting English publications from the period between 2013 and 2023. Keywords including "electroencephalogram," "brain," "disease," and "detection" guided the search. Post-extraction, the data was meticulously cleaned to remove any duplications and confirm the focus on EEG's role in identifying Brain Diseases (BD). The resulting collection of papers was then organized into an Excel CSV file for comprehensive analysis.

2.2 Data analysis

The keyword co-occurrence analysis in this study was performed using the VOSviewer tool, version 1.6.19, from Leiden University's Center for Science and Technology Studies. Data cleaning was conducted in Excel using its thesaurus function to minimize redundant data. Analysis was carried out using RStudio 2023.03.0-386, recognized for its statistical capabilities, in collaboration with the Department of Economics and Statistics at the University of Naples Federico II. The study's main aim is to explore current trends in scholarly publications.

3 Result and Discussion

3.1 Data searches

Using the search terms "electroencephalogram," "brain," "disease," and "detection" in Scopus, 388 papers were identified. However, 195 were discarded as they were not within the recent ten-year scope (2013-2023) or relevant article categories, emphasizing the commitment to using the most current and accurate data. Consequently, 193 papers were selected for the bibliometric study.

This bibliometric study, utilizing the esteemed Scopus database, aims to depict knowledge concepts related to EEG in BD diagnosis both precisely and visually [28]. It encompasses performance analysis and scientific mapping: the former evaluates contributions from international scholars and institutions, while the latter clarifies the research's conceptual framework and future trajectories [29]. The study also articulates the complex interplays among various research elements and their cohesive strengths, as detailed in the publication criteria listed in Table 1.

Table 1. Criteria for the selection of the publications.

Criteria	Value
Data Source	Scopus
Search Terms	"electroencephalogram" AND "brain" AND "disease" AND "detection"
Publication Period	January 2013 – September 2023
Document Type	The article
Language	English
Number of articles	193/(388)

3.2 Publication trend

The RStudio software package was used to create visual representations of the temporal distribution of published data, as shown in Figure 1 and Table 2. The analysis sheds light on the changing patterns of publication over time. On average, each paper received six citations per year, with an overall average of 17.55 papers published annually. The year 2022 stands out with 37 publications, marking it as the year with the highest scholarly output. In contrast, 2020 was significant for generating 22 papers and had the highest average citation per paper and per year, underlining the importance and influence of research in that period. Kraus et al. (2014) suggest that a high number of citations in a paper is indicative of its scientific impact and lays the groundwork for future research [29].

3.3 Analysis of the contributing country

Table 3 and Figure 2 detail the leading countries in EEG research for BD detection, with China at the forefront with 45 articles. The United States follows with 21, India with 19, Japan with 10, and Australia with 9. The table distinguishes between research produced within one country and collaborative international efforts.

Table 2. Publication of data trends by year using the RStudio application

Year	Number of Articles	Mean Total Citation per Article	Mean Total Citation per Year	Citable Year
2013	13	27.92	2.54	11
2014	9	26.56	2.66	10
2015	18	26.44	2.94	9
2016	5	11.8	1.48	8
2017	6	29.67	4.24	7
2018	13	30.46	5.08	6
2019	12	26.58	5.32	5
2020	22	31.27	7.82	4
2021	29	9.03	3.01	3
2022	37	5.49	2.74	2
2023	29	1.76	1.76	1
Average	17.55	20.63	3.6	6

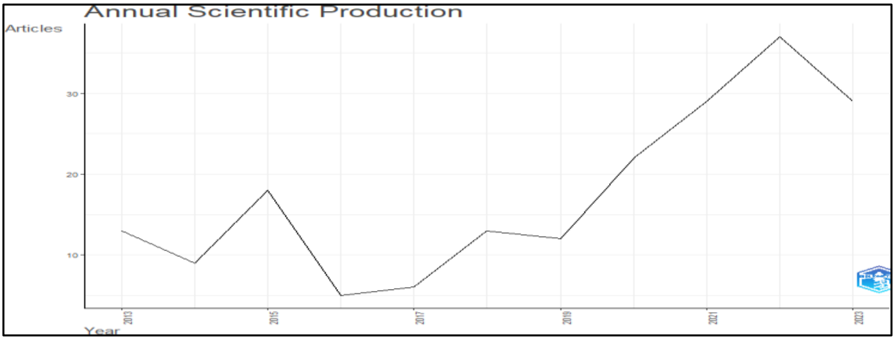

Fig. 1. Annual scientific publication

Table 3. The most impactful countries

Country	Number of Articles	Single Country Production	Multiple Country Production
China	45	38	7
USA	21	17	4
India	19	19	0
Japan	10	7	3
Australia	9	4	5

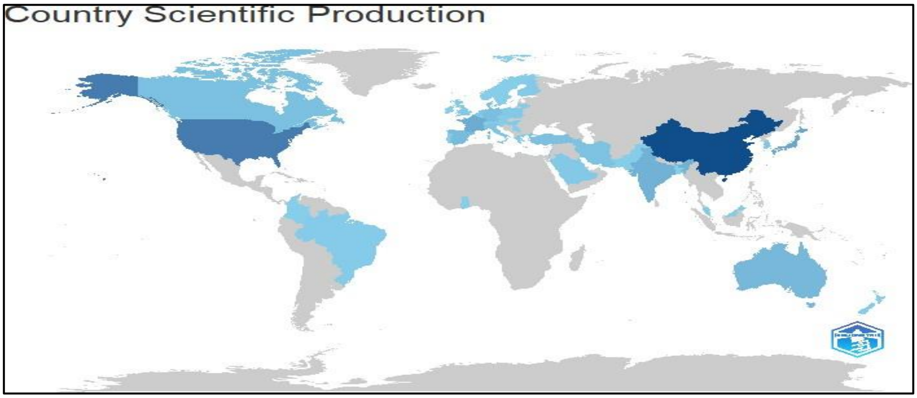

Fig. 2. Globe heatmap of countries

3.4 Analysis of the contributing institution

The co-authoring index reveals Harvard Medical School in the United States as the top institution in EEG research for BD detection with 19 articles. Queensland University of Technology in Australia, Shandong Normal University, and Fudan University in China follow with 12 publications each, with Fudan University alone contributing 11 pieces.

Table 4. The institution that demonstrates the utmost productivity with the RStudio application

No.	Institution	Country	Documents
1.	Harvard Medical School	USA	19
2.	Queensland University of Technology	Australia	12
3.	Shandong Normal University	China	12
4.	Tianjin University	China	12
5.	Fudan University	China	11

3.5 Analysis of the contributing source

Table 5 indicates "Biomedical Signal Processing and Control" as the most cited publication in EEG research for BD detection, with 11 documents and 249 citations, yielding an H-index of 6. This highlights its productivity and impact in the field. Other notable sources include "Computers In Biology and Medicine" with 73 citations from 7 documents, "IEEE Journal of Biomedical and Health Informatics" with 149 citations from 7 papers, and "IEEE Transactions on Neural Systems and Rehabilitation Engineering" with 249 citations from 6 documents. "Brain and Development" also features with 35 citations across five papers.

Figure 3 illustrates the connections among author affiliations (AU_UN), sources/journals (SO), and author nations (AU_CO), where the size of rectangles in the visualization corresponds to the number of associated entities, showing the degree of their contribution and collaboration. The analysis suggests that countries, particularly China, have been actively disseminating their research through various prestigious channels, including "Nature Communication" and "IEEE Transactions on Neural Systems and Rehabilitation Engineering," among others.

Table 5. The most productive and influential source using the RStudio application

Source	Documents	Citations	H-index
Biomedical Signal Processing and Control	11	158	6
Computers In Biology and Medicine	7	73	4
IEEE Journal of Biomedical and Health Informatics	7	149	4
IEEE Transactions on Neural Systems and Rehabilitation Engineering	6	249	4
Brain and Development	5	35	4

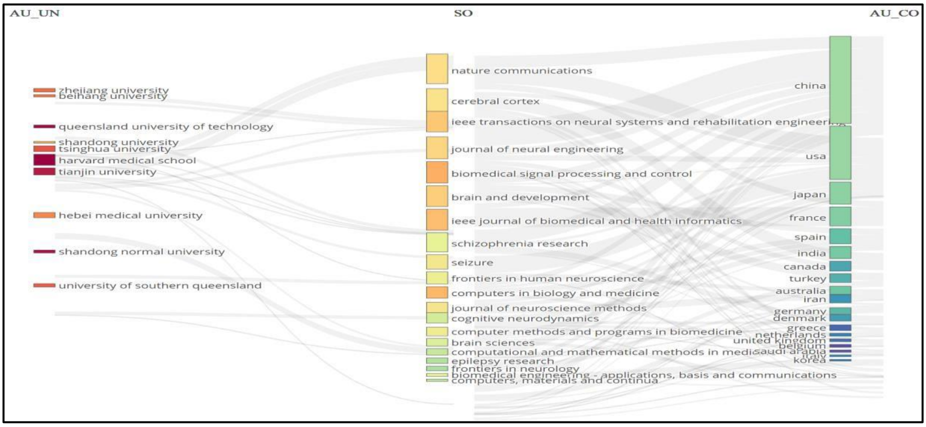

Fig. 3. Three-field plot between author affiliations author's country (AU_CO), journals (SO),and author affiliation (AU_UN) using the RStudio application

3.6 Analysis of contributing author

Table 6 presents authors with significant contributions to EEG research for BD detection. Wang J from Fudan University leads with eight articles and 171 citations, boasting an H-index of 5. Li Y from the University of Southern Queensland follows with seven articles and 275 citations, also holding an H-index of 5, marking them as the second most impactful author in this domain. Zhang X from Henan Polytechnic University has authored seven works with 144 citations and an H-index of 4, ranking third in terms of influence and productivity.

Table 6. The most prolific author using the Rstudio application

Author	Total Docs	Citations	H-index	Affiliation
Wang J	8	171	5	Fudan University
Li Y	7	275	5	University of Southern Queensland
Zhang X	7	144	4	Henan Polytechnic University
Acharya Ur	6	277	4	University of Southern Queensland

3.7 Analysis of contributing paper

The citation count of an academic article reflects its significance and impact within a field. In EEG research for BD diagnosis, the frequency of citations is indicative of a study's contribution and relevance. Data from RStudio confirms that the most impactful articles, as evidenced by citation counts, were produced by a collective effort of 193 papers, details of which are displayed in Table 7.

Table 7. Most cited articles using the RStudio application

Author	Title	Source	Total Citation
[34]	A deep learning approach for Parkinson's disease diagnosis from EEG signals	Neural Computing and Applications	243
[35]	Epileptic Seizure Detection in EEG Signals Using a Unified Temporal- Spectral Squeeze-and-Excitation Network	IEEE Transactions on Neural Systems and Rehabilitation Engineering	123
[31]	Deep Multi-View Feature Learning for EEG-Based Epileptic Seizure Detection	IEEE Transactions on Neural Systems and Rehabilitation Engineering	96
[32]	Epileptic seizure detection based on imbalanced classification and wavelet packet transform	Seizure	89

The 2020 article by Oh et al., cited 243 times, is pivotal in EEG research for Parkinson's disease (PD), offering a CNN model for PD diagnosis based on EEG signals. The study capitalized on EEG's ability to detect early brain abnormalities by using signals from 20 PD patients and 20 non-PD individuals. The developed CNN, with 13 layers, bypassed traditional feature representation and achieved 88.25% accuracy, 84.71% sensitivity, and 91.77% specificity, showing promise for broader clinical application [34].

Li et al.'s 2020 paper, "Epileptic Seizure Detection in EEG Signals Using a Unified Temporal-Spectral Squeeze-and-Excitation Network," cited 123 times, introduces an innovative EEG seizure detection framework. The CE-stSENet leverages spectral-temporal analysis for feature integration and employs a unique loss function to address overfitting. This model outperformed existing methods in tests on three EEG datasets, proving its proficiency in identifying epileptic seizures [35].

The 2019 article by Tian et al., titled "Deep Multi-View Feature Learning for EEG-Based Epileptic Seizure Detection," cited 96 times, proposes a novel multi-view deep feature extraction method for improving EEG-based seizure detection. The method employs FFT and WPD to generate features, which are then processed by a CNN to reduce dimensionality and enhance recognition accuracy. A Takagi-Sugeno-Kang fuzzy system based on these features results in a highly generalizable classification model, which outperforms traditional methods in terms of classification accuracy at least 4% greater [31].

Yuan et al.'s 2017 article, "Epileptic seizure detection based on imbalanced classification and wavelet packet transform," cited 89 times, addresses the challenge of detecting seizures in imbalanced EEG data. The study presents a weighted extreme learning machine (ELM) algorithm that analyzes EEG features via wavelet packet transform and a pattern match regularity statistic, improving seizure detection in clinical EEG recordings. This method shows promise for clinical adoption and further testing with continuous EEG data is planned [32].

Table 8. Review of BD Detection by Electroencephalogram

Type of BD	Methods and Measured Parameters	Results	References
Parkinson's Disease (PD)	The research employed EEG signals to train a CNN model to distinguish PD patients from healthy individuals by analyzing brainwave patterns. The model's diagnostic effectiveness was gauged by accuracy, sensitivity, and specificity. Additionally, the CNN's learned features and its computational demands were evaluated for potential real-world application scalability.	The CNN model was able to diagnose PDmore accurately (88.25%), moresensitively (84.71%), and more specifically (91.77%). The study revealed that the CNN model accurately diagnosed Parkinson's Disease with high precision, outperforming traditional SVM and ANN methods. It effectively differentiated PD EEG patterns through key features like frequency and complexity, proving efficient for real-time and large-scale applications due to lower memory and computational requirements.	[34]
EpilepticSeizure	The paper presents the CE-stSENet model for automatic seizure detection in EEG data, which combines temporal and spectral analysis with maximum mean discrepancy for improved differentiation. It was evaluated using various performance metrics on Bonn, TUSZ, and CHB-MIT datasets. The model excels in identifying seizure-specific EEG patterns, thereby advancing seizure detection technology.	The study demonstrates that the CE-stSENet model sets a new standard in epileptic seizure detection, surpassing previous deep learning and conventional models. It captures EEG signal characteristics both in the spectral and temporal domains and maintains data integrity. The model also effectively prevents overfitting, a common challenge with limited seizure data, by employing an MMD-based loss function to maximize information extraction.	[35]

Type of BD	Methods and Measured Parameters	Results	References
EpilepticSeizure	The article details a novel approach for extracting features from EEG data for seizure detection using FFT and WPD to capture signal characteristics, which are then enhanced by a CNN for depth and dimensionality reduction. The refined features are utilized by a MV-TSK-FS classifier for high accuracy. Key parameters include the detailed capture of signal aspects by FFT and WPD, the dimensionality reduction by CNN, and the classification accuracy of MV-TSK-FS. Performance is quantified through sensitivity, specificity, and accurate detection of seizure onset.	The article demonstrates that the proposed multi-view feature extraction method achieves superior classification accuracy over traditional methods like PCA, FFT, and WPD. It effectively identifies key seizure characteristics, resulting in a robust and intelligible classification model. The method also scores high sensitivity(96.66±0.14%),specificity (99.14±0.14%), accuracy (98.33±0.18%), latency (1.0431 s), and sensitivity as measured by onsets (99.95%). These results are higher than those obtained using standard feature extraction methodssuch as PCA, FFT, and WPD alone or single-view deep features.	[31]
EpilepticSeizure	The article discusses the use of a radial basis function neural network to detect high-frequency oscillations (HFOs) in the 80-500 Hz range from long-term EEG recordings of 15 patients with focal epilepsy. The parameters measured were the rate of HFOs (occurrences per minute), HFO duration (average length in milliseconds), HFO amplitude (average peak-to-peak measurement in microvolts), and HFO frequency (average frequency in hertz).	The study's results revealed a higher rate of HFOs in brain regions involved in seizure onset and an increase in HFO rate in the temporal and parietal areas during certain sleep stages, with no such increase in frontal regions. There was no significant difference in HFO characteristics like length, amplitude, or frequency related to seizure initiation zones or sleep stages. The HFO rate was positively linked with daily seizure frequency and inversely with time to next seizure, suggesting potential as a biomarker for epileptogenicity and seizure forecasting. The findings also indicated the sleep-wake cycle's varied effects on HFO modulation across different brain regions.	[36]
Autism spectrum disorder (ASD)	The study described in the article employed the PyCaret framework, a machine learning library, to detect anomalies in EEG signals from children with autism and typically developing children. This methodology suggests a data-driven approach to better understand and distinguish the neural patterns associated with autism.	In the study, the researchers discovered that the Angle-Based Outlier Detection (ABOD) module was the most effective in identifying anomalies within EEG signal data. The study's findings further suggest that EEG-based anomaly detection methods could be instrumental in the early identification of Autism Spectrum Disorder (ASD). The research demonstrates the potential of using EEG-based anomaly detection to pinpoint early biomarkers for ASD. Overall, the study provides significant insights into the application of EEG signals and anomaly detection methods in the diagnosis and treatment of ASD.	[37]

Type of BD	Methods and Measured Parameters	Results	References
EpilepticSeizure	This article presents an innovative technique for managing epilepsy involving an implanted device to monitor and stimulate the brain. A handheld device and cloud computing resources are also utilized to assess and regulate the therapy. The article states that the implanted device measures the EEG parameters, which encompass: - The iEEG data were recorded from 16 electrodes placed in various brain areas. - Power spectral density (PSD) analysis of intracranial electroencephalogram (iEEG) signals over several frequency ranges. - Interictal epileptiform discharges (IEDs) refer to atypical spikes or waves observed in the intracranial electroencephalogram (iEEG). - High-frequency oscillations (HFOs) refer to rapid and intense fluctuations in the intracranial electroencephalogram (iEEG). - Seizure onset zones (SOZs) refer to specific areas in the brain where seizures originate.Seizure propagation patterns refer to the specific routes through which seizures spread inside the brain. Duration, frequency, and intensity of seizures	The article highlights a sophisticated epilepsy management system involving an implantable device that: - Continuously captures and transmits intracranial EEG (iEEG) data to both a handheld device and cloud-based storage. - Enables real-time analysis and categorization of iEEG through machine learning on the portable device and cloud. - Delivers electrical brain stimulation governed by set or adaptable protocols to manage brain activity. - Modulates brain activity to potentially reduce the frequency and severity of seizures. - Provides ongoing feedback to patients and physicians about the disease status and treatment efficacy. - Offers promise as a personalized, adaptive treatment platform, particularly for individuals with drug-resistant focal epilepsy, aiming to improve their quality of life.	[38]
Autism spectrum disorder (ASD)	The author used longitudinal EEG power readings from 3 to 36 months old in either low- or high-risk babies with ASD to see how and when power can tell the difference between ASD risk and diagnosis by age three years. The authors measured EEG power in four frequency bands: delta, theta, alpha, and gamma. They did this in different parts of the brain and at various stages of growth. They used data-based models to find the best combinations of EEG power features to tell the difference between ASD diagnoses and other results.	The article concluded that: - EEG power patterns in the first year of life are highly indicative of ASD, differentiating it from other developmental outcomes. Specifically, delta and gamma frequencies were consistently distinct in infants later diagnosed with ASD. - Over time, there's a noticeable shift towards reliance on higher frequency powers for outcome differentiation. Notably, low alpha and gamma growth rates over the span of three years were significant markers for ASD diagnosis. - These insights underscore the potential of early-life EEG power assessment as a diagnostic tool for Autism Spectrum Disorder. They also emphasize the importance of the timing and progression of development in understanding ASD's etiology.	[39]

Type of BD	Methods and Measured Parameters	Results	References
Dravet syndrome	The study described in the article focused on using EEG signals to detect Dravet syndrome in mice with a deficiency in the Nav1.1 gene. The researchers measured several EEG parameters such as spike frequency, amplitude, duration, area, and specific waveforms like sharp wave, polyspike, and spike-and-wave. They further analyzed the EEG for power spectrum, coherence, and phase synchronization across different brain areas during rest and social interaction. Additionally, the mice were subjected to behavioral tests assessing social preference and spatial memory, including the Morris water maze.	In the EEG study, mice with Nav1.1 haploinsufficiency, which is associated with Dravet syndrome, showed significantly higher spike frequency, amplitude, duration, and area in their EEG readings compared to controls. They also exhibited more frequent occurrences of complex spike waveforms such as polyspike and spike-and-wave patterns. These mice demonstrated reduced EEG power in theta and gamma frequencies, less coherence between the hippocampus and other brain areas, and lower phase synchronization in the gamma band, especially during social interaction. Additionally, these mice showed less social behavior and impaired spatial learning and memory. This research suggests that EEG could be an effective tool for diagnosing Dravet syndrome due to the clear disruption in brain network activity and cognitive function caused by the Nav1.1 deficiency.	[40]
Schizophrenia	The article discusses a diagnostic method for schizophrenia using EEG and deep learning to differentiate patients from healthy individuals. EEG data is converted into visual time-frequency representations through continuous wavelet transform (CWT), and these images are analyzed by four pre-trained CNNs—AlexNet, ResNet-18, VGG-19, and Inception-v3—to extract features. These features are then classified by a support vector machine (SVM), with optimized parameters via grid search, to accurately identify schizophrenia.	The study presents a method for diagnosing schizophrenia using EEG signals, showing high accuracy, sensitivity, and specificity when tested on 14 healthy individuals and 14 schizophrenia patients. Utilizing EEG data from the frontal, central, parietal, and occipital brain regions with a ResNet-18-SVM model yielded the best results, achieving an accuracy of 98.60%, sensitivity of 99.65%, and specificity of 96.92%. The findings suggest that this method outperforms other existing diagnostic approaches and could be a reliable tool for the early detection and management of schizophrenia.	[41]
Attention Deficit Hyperactivity Disorder (ADHD)	The authors presented a novel method to identify individuals with ADHD using a serious game that captures EEG data. They analyzed the EEG signals for power spectral density (PSD) and event-related potentials (ERP), which reflect brain activity distribution and response to stimuli, respectively. For data collection, participants wore a wireless EEG headset with 14 electrodes capturing activity from the brain's key regions: frontal, temporal, parietal, and occipital regions	The study showed high accuracy in using EEG data to identify ADHD, with machine learning differentiating control types in a game and ADHD diagnoses. Achieving up to 96% accuracy for game control and 98% for ADHD identification, the method outperforms existing ones in precision. The approach offers a non-invasive tool for recognizing and potentially improving attention in individuals with ADHD.	[42]

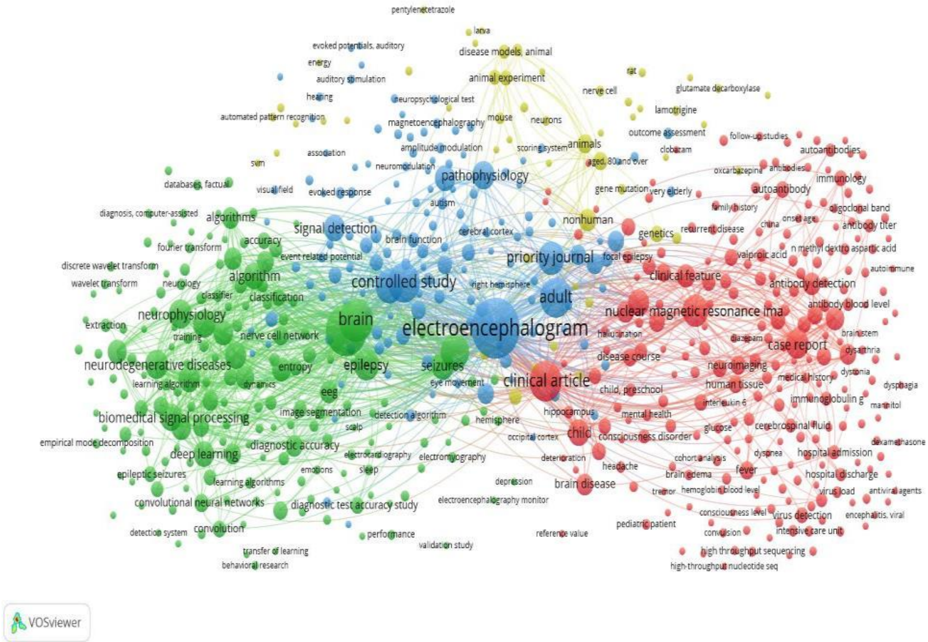

Fig. 4. Visualization topic area by VOSviewer using network visualization

3.8 Analysis of keyword co-occurrence

The study applied VOSviewer software to analyze keyword co-occurrence from collected articles, aiming to enhance the identification and classification of topics in EEG-based research for Bipolar Disorder (BD) detection. It employed a full counting method to quantify the prevalence of keywords, reflecting their cumulative frequency in the literature. The visual network produced by VOSviewer, illustrating the relationships between topics, is shown in Figure 4 of the study.

The VOSviewer analysis delineated four clusters, showing the interconnectedness of topics within EEG research for BD detection. It employed color-coding to represent keyword frequency in titles and abstracts, with the sizes of circles and letters indicating frequency. A corpus of 193 relevant articles yielded 632 keywords, with "electroencephalography" and "electroencephalogram" being the most common, reflecting advancements in the field as visualized in Figure 4.

4 Conclusion

A bibliometric analysis found that 193 scholarly papers have examined how electroencephalography (EEG) can be used to find BDs. The average annual publication count was found to be 17.55. However, the average number of citations per publication had a significant value of 20.64. The performance analysis results show that China emerged as the most influential nation. Harvard Medical School was the institution with the highest productivity level, with 19 papers. The source that demonstrated the highest level of productivity was the journal "Biomedical Signal Processing and Control," which published 11 articles and gained a notable 158 citations. In contrast, the "IEEE Transactions on Neural Systems and Rehabilitation Engineering" emerged as the most prominent source of influence, with a noteworthy contribution of 6 publications and 249 citations. A comprehensive scientific mapping analysis has determined that Wang J has made a significant scholarly contribution, as shown by an H-index of 5 and a total of 171 citations derived from 8 distinct articles. The scholarly article written by Oh et al. in 2020 [34] has garnered considerable recognition, seen by its notable citation total of 243. The most commonly occurring keyword is "electroencephalogram."

Through bibliometric science mapping analysis, researchers can strategically devise, contemplate, and formulate prospective avenues of research about the potential application of electroencephalography (EEG) in identifying BDs. However, this

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