Automated Detection of Neurological and Mental Health Disorders Using EEG Signals and Artificial Intelligence: A Systematic Review

Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery

WILEY

WIREs DATA MINING AND KNOWLEDGE DISCOVERY

SYSTEMATIC REVIEW OPEN ACCESS

Automated Detection of Neurological and Mental Health Disorders Using EEG Signals and Artificial Intelligence: A Systematic Review

Hakan Uyanik[1] | Abdulkadir Sengur[2] | Massimo Salvi[3] | Ru-San Tan[4,5] | Jen Hong Tan[6] | U. Rajendra Acharya[7,8]

[1]Electrical-Electronics Engineering Department, Engineering Faculty, Munzur University, Tunceli, Turkey | [2]Electrical-Electronics Engineering Department, Technology Faculty, Firat University, Elazig, Turkey | [3]Biolab, PoliToBIOMed Lab, Department of Electronics and Telecommunications, Politecnico di Torino, Torino, Italy | [4]Department of Cardiology, National Heart Centre Singapore, Singapore, Singapore | [5]Duke-NUS Medical School, Singapore, Singapore | [6]Data Science and Artificial Intelligence Lab, Singapore General Hospital, Singapore, Singapore | [7]School of Mathematics, Physics and Computing, University of Southern Queensland, Springfield, Australia | [8]Centre for Health Research, University of Southern Queensland, Springfield, Australia

Correspondence: Abdulkadir Sengur (ksengur@firat.edu.tr)

Received: 7 November 2024 | **Revised:** 28 January 2025 | **Accepted:** 3 February 2025

Associate Editor: Elisa Bertino | **Editor-in-Chief:** Witold Pedrycz

Funding: The authors received no specific funding for this work.

Keywords: artificial intelligence | clinical decision support system | EEG | mental health | neurological health

ABSTRACT

Mental and neurological disorders significantly impact global health. This systematic review examines the use of artificial intelligence (AI) techniques to automatically detect these conditions using electroencephalography (EEG) signals. Guided by Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA), we reviewed 74 carefully selected studies published between 2013 and August 2024 that used machine learning (ML), deep learning (DL), or both of these two methods to detect neurological and mental health disorders automatically using EEG signals. The most common and most prevalent neurological and mental health disorder types were sourced from major databases, including Scopus, Web of Science, Science Direct, PubMed, and IEEE Xplore. Epilepsy, depression, and Alzheimer's disease are the most studied conditions that meet our evaluation criteria, 32, 12, and 10 studies were identified on these topics, respectively. Conversely, the number of studies meeting our criteria regarding stress, schizophrenia, Parkinson's disease, and autism spectrum disorders was relatively more average: 6, 4, 3, and 3, respectively. The diseases that least met our evaluation conditions were one study each of seizure, stroke, anxiety diseases, and one study examining Alzheimer's disease and epilepsy together. Support Vector Machines (SVM) were most widely used in ML methods, while Convolutional Neural Networks (CNNs) dominated DL approaches. DL methods generally outperformed traditional ML, as they yielded higher performance using huge EEG data. We observed that the complex decision process during feature extraction from EEG signals in ML-based models significantly impacted results, while DL-based models handled this more efficiently. AI-based EEG analysis shows promise for automated detection of neurological and mental health conditions. Future research should focus on multi-disease studies, standardizing datasets, improving model interpretability, and developing clinical decision support systems to assist in the diagnosis and treatment of these disorders.

1 | Introduction

In the statement of the World Health Organization (WHO) data, a 2019 study determined that ~970 million people worldwide, or 1 in every 8, have at least one mental disorder, with anxiety and depression being the most common (Mental-disorders n.d.; Institute of Health Metrics and Evaluation n.d.). These problems affect many vital functions, physical health, thinking, and emotional cycles. Mental disorders come in many different types, and it is possible to minimize them with effective precautions and treatments. However, many people with these problems worldwide cannot access these precautions and treatments.

According to the WHO's 2023 data, 3.8% of the population has depression, with higher rate in adults (5%) and those over 60 (5.7%). This number corresponds to ~280 million people worldwide (Global Health Data Exchange (GHDx) n.d.). These numbers are 50% higher in women than in men. The biggest factor in this rate difference is that pregnant women and women who have just given birth are more prone to depression (Woody et al. 2017). It is a disease directly related to suicide. For example, it is one of the leading causes of suicide, and suicide is the fourth leading cause of death for people aged 15–29 worldwide, with more than 700,000 young people losing their lives each year (World Health Organization (WHO) n.d.-a). Like depression, anxiety is among the most common mental illnesses worldwide. The prevalence rate of this disease is 4% worldwide (Global Health Data Exchange n.d.). According to 2019 data, approximately 301 million people suffer from this disease. Although there are very effective treatment methods for this disease, only one in every four people (27.6%) who need these treatments can access them (World Health Organization n.d.; Alonso et al. 2018). Due to the COVID-19 pandemic in 2020, there has been a remarkable increase in the number of people suffering from these two diseases worldwide. According to preliminary findings, there was increase in anxiety and major depression levels of 26% and 28%, respectively, in 1 year (Mental Health and COVID-19 2022). According to 2019 data, ~1 in 150 people in the world (40 million people or 0.53% of the world's population) have bipolar disorder (*Lancet Psychiatry* 2022). The treatment coverage of this disease is limited worldwide. Misdiagnosis is quite common in both gender groups. People suffering from this disease have difficulty accessing treatment, usually in low- and middle-income countries (LMICs). Stigmatization and discrimination against people suffering from this disease by society and health institutions are frequent events. People with this disease have tense relationships, various problems at school or work, and difficulty in performing daily activities (World Health Organization (WHO), n.d.-b). This disease may cause an increase in the risk of suicide, anxiety, and substance use. Hence, people with this disease die an average of 10 years earlier than the general population (Chan et al. 2022).

Although schizophrenia is not as common as the diseases listed above, it is one of the mental illnesses that most affect the quality of life, health, and therefore life expectancy. The number of people suffering from this illness worldwide has been 24 million or 1 in 300 people (0.32%) as of 2022. This rate is higher among adults (1 in 222 people or 0.45%) (Global Health Data Exchange (GHDx), n.d.). The onset of this disorder mostly shows up in late adolescence and the twenties, and this occurrence tends to be earlier in men than in women. People with this illness are two to three times more likely to die than the general population (Laursen et al. 2014). Schizophrenia causes persistent cognitive impairments (Harrison et al. 2001) and severe stigmatization, leading to social exclusion and increased vulnerability to human rights violations (World Health Organization (WHO) n.d.-c). Treatment access is limited, with schizophrenia accounting for approximately half of the mental hospital patients (World Health Organization (WHO) 2009), yet only 31.3% of psychotic patients receive care (Jaeschke et al. 2021).

Early and accurate diagnosis of neurological and mental illnesses is critical for effective and accurate treatment. Thus, the devastating effects of mental illnesses, some of which are described above, on individuals and society can be minimized. Conventionally, neurological and mental health disorders are diagnosed through clinical interviews, standardized questionnaires, neuropsychological tests, and sometimes neuroimaging techniques. However, these traditional methods face several limitations. These include subjectivity in clinical interviews and self-report measures, the time-consuming nature of comprehensive assessments, resource-intensive procedures like MRI (Magnetic Resonance Imaging) or PET (Positron Emission Tomography) scans, variability in clinical expertise, and difficulties in the early detection of subtle changes (Lin et al. 2017).

Recently, artificial intelligence-based models have been used by expert groups, including psychologists and psychiatrists, to assist the experts in decision-making by using various types of data of patients (medical records, behavioral data, social media usage, etc.). Especially recently, very high success rates have been achieved with ML and DL methods, which have experienced an explosion in development (Su et al. 2020).

ML can be defined as a subfield of AI that can perform classification, regression, and clustering tasks (Mitchell and Mitchell 1997). DL, a sub-branch of ML, is a group of techniques that can process various data (text, images, strings, etc.) in a raw form and automatically detect feature sets that determine the categories of these data. Since it performs these operations automatically, there is no need to define the properties. Recently, many studies have shown high performance using DL in mental health (Shanthalakshmi Revathy et al. 2024; Wang, Zhao et al. 2024; Das and Naskar 2024; Ajith et al. 2024; Uyulan et al. 2021; Uddin et al. 2022; Kim, Lee, Park et al. 2020; Al Banna et al. 2023).

Among the various neuroimaging techniques developed to study brain function, electroencephalography (EEG) is found to be a useful tool for investigating neurological and mental health diseases. The high temporal resolution of EEG helps to capture rapid brain activity changes, which are essential to understanding the dynamic nature of these conditions. The EEG signals are non-invasive, economical, and suitable for widespread clinical use across diverse patient populations. Unlike other neuroimaging techniques, EEG directly measures neuronal activity, providing a more immediate representation of brain function (Khosla et al. 2020).

Systematic review articles based on DL and ML methods of neurological and mental disorders are generally

prepared specifically for a single disease, such as depression (Yasin et al. 2023), Alzheimer's disease (Harshini and Thangarajan 2024), epilepsy (Yuan et al. 2022), stress (Zhou et al. 2021), schizophrenia (Rahul et al. 2024) and Parkinson's disease (Sigcha et al. 2023). This systematic study was conducted to address the need for a more comprehensive review that considers more than one disease. Thus, more detailed information about diseases will be provided to better identify deficiencies in the studies conducted in this area, and comparisons between diseases will be possible.

In this study, a systematic mapping study was conducted with 74 meticulously selected primary studies. Our aim is to provide current, accurate AI approaches for detecting neurological and mental health disorders using EEG signals and (ii) identify research gaps and future directions in this expeditiously evolving field.

2 | Background

2.1 | Mental Disorders

Today, there are over 200 classified types of mental disorders. The most common of these disorders are depression, bipolar disorder, schizophrenia, and anxiety. There are many common and distinctive symptoms that exist among these illnesses (Mental Health America n.d.). Although neurological and mental disorders are very diverse, the most common types were considered in this study. The most dangerous diseases, as well as the diseases that affect daily life are included in the scope of the study. A diagram of the types of neurological and mental disorders is given in Figure 1. In the next subsections, the clinical information regarding neurological and mental disorders is provided.

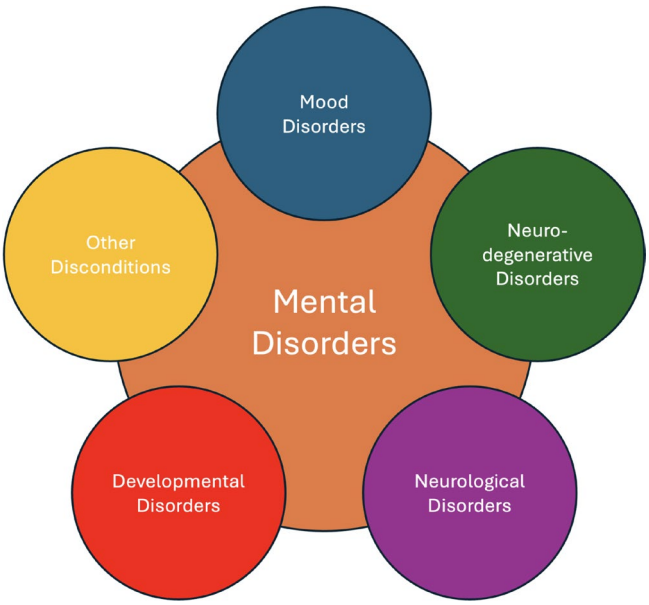

FIGURE 1 | An illustration of the neurological and mental disorder types.

2.1.1 | Mood Disorders

This group of psychiatric illnesses can affect patients' emotions, energy, and motivations simultaneously (Rakofsky and Rapaport 2018). These disorders can deeply impact daily activities, relationships, and overall quality of life. They range from persistent low moods to extreme emotional fluctuations and excessive worry or fear. While each disorder has its unique features, they often share overlapping symptoms and can co-occur, presenting complex challenges for diagnosis and treatment. In this study, Major Depressive Disorder (MDD) (Fava and Kendler 2000), Bipolar Disorder (Grande et al. 2016), Bipolar Depression (Malhi et al. 2003), Bipolar Mania (Li, Yuan et al. 2023), Anxiety (Saxena and Krug 2013; Chellappa and Aeschbach 2022), Anhedonia (Serretti 2023) and Stress (Cohen et al. 2007) are considered.

2.1.2 | Neurodegenerative Disorders

Neurodegenerative disorders are chronic, progressive disorders characterized by the selective loss of neurons in the central nervous system that mostly affect older adults (Singh et al. 2021). These disorders typically involve the loss of neurons and can affect various aspects of a person's life, including movement, cognition, and behavior. They are often age-related and can have devastating effects on patients and their families. Due to the complex and variable nature of these disorders, they present significant challenges in diagnosis and treatment. In this review, we have considered Alzheimer's disease (AD) (Masters et al. 2015), Parkinson's disease (PD) (Tolosa et al. 2021), Lewy Body Disease (Kalra 1996), Multiple Sclerosis (Ford 2020), Huntington's disease (HD) (Ross et al. 2014) and Amyotrophic Lateral Sclerosis (ALS) (Hardiman et al. 2017).

2.1.3 | Neurological Disorders

Diseases in this group are the leading cause of disability and the second leading cause of death worldwide. While there has been a significant increase in the number of people suffering from this disease, especially in the last 30 years, these numbers are expected to increase further on a global scale due to the population growth rate and aging (Feigin et al. 2020). These disorders often lead to significant impairments in cognitive function, motor control, and sensory processing. In this review, we have included Stroke (Feigin et al. 2023), Traumatic Brain Injury (TBI) (Maas et al. 2022), Seizures (Bruno et al. 2020), and Focal Cortical Dysplasia (FCD) (Blumcke et al. 2017) groups.

2.1.4 | Developmental Disorders

Developmental disorders and childhood learning difficulties are defined as complex constellations of relative strengths and weaknesses in a child's learning, cognition, and behavior that occur early in a child's development (Astle and

Fletcher-Watson 2020). These disorders can have lifelong impacts on an individual's ability to learn, socialize, and function independently. While the exact causes of many developmental disorders are not fully discovered, often they involve a complex interplay of genetic and environmental factors. Autism Spectrum Disorder (ASD) (Lord et al. 2020) and Attention Deficit/Hyperactivity Disorder (ADHD) (Berger 2011) are considered in this review.

2.1.5 | Other Mental Health Conditions

This category encompasses a diverse range of mental health disorders that, while distinct from mood and developmental disorders, seriously impact an individual's cognitive processes, emotional regulation, and behavior. These conditions often involve complex interactions between genetic predisposition, environmental factors, and neurobiological changes. Schizophrenia (Chaiyakunapruk et al. 2016; Rantala et al. 2022), Obsessive Compulsive Disorder (OCD) (Perera et al. 2023), Post Traumatic Stress Disorder (PTSD) (Yehuda et al. 2015; Kessler and Wang 2008) and Psychosis/Psychopathy (Fisher et al. 2024; Thomson et al. 2019; Wong and Olver 2015; Johanson et al. 2020; Bell et al. 2022) are considered in this group.

2.2 | Electroencephalography

The field of electroencephalography deals with the recording of electroencephalograms (EEGs) and the interpretation of these recordings. An electroencephalogram is a record of electrical signals occurring as a result of cooperative electrical activities of neurons in the brain, or in other words, synchronized electrical activities occurring in brain cells as a time series in the form of extracellular field potentials. EEG signals can be measured through electrodes placed on the scalp or directly measured on the cerebral cortex (Electrocorticogram-ECoG). Electric fields that are measured intracortically are called Local Field Potentials (LFP). While EEG signals measured without an external stimulus are called spontaneous EEG, EEG signals that occur due to external or internal stimuli are called Event-Related Potentials (ERP). The amplitudes of EEG signals measured from the scalp of a normal person while awake are expected to be between 10 and 100 mV. This situation reaches amplitudes of 500 to 1500 mV in the cortex of individuals with epilepsy (Blinowska and Durka 2006).

EEG signals are distinguished by five basic rhythms (sub-rhythms): delta (0.5 ~ 4 Hz), theta (4 ~ 8 Hz), alpha (8 ~ 13 Hz), beta (13 ~ 30 Hz), and gamma (> 30 Hz) sub-rhythms. Each rhythm has distinctive characteristics, and its contribution to the EEG signal varies depending on the age, behavioral state, and especially the state of alertness of the subject being measured. A few basic features of sub-rhythms are listed below:

- Delta: During deep sleep, its amplitude is around 75–200 mV and is present in almost every part of the scalp where it is measured.
- Theta: This sub-rhythm is rarely seen in adult humans. However, it is dominant in rodents.
- Alpha: This sub-rhythm is dominant during wakefulness. These signals are more commonly observed in the back of the head. It is at its most intense when the eyes are closed and in a comfortable position. It is weak at moments when attention is required (when observing carefully with the eyes, when mental effort is intense).
- Beta: Many studies conducted on animals and humans have observed that this sub-rhythm is evident in states of alertness and focused attention.
- Gamma: It is a sub-rhythm whose effectiveness increases during the information processing and implementation of voluntary movements. In cases where information processing increases, the oscillation in this sub-rhythm also increases.

EEG signals are today the most preferred biomarker data among brain-related studies due to the many advantages they offer, such as low-cost acquisition, multi-channel structure, high temporal resolution, and the size of measurement devices becoming more compact day-by-day (Khosla et al. 2020).

With a high temporal resolution, today these biomarkers measure with a 5000 Hz sampling rate, enabling continuous in-depth analysis of brain functions with high sample imaging. In addition, although a complete spatial brain map is obtained with MRI and PET imaging techniques, these methods only provide a static brain image (Rivera et al. 2022).

Compared to NIRS (Near Infrared Spectroscopy) signals, EEG signals are better than these signals in terms of response time (command execution) and temporal resolution (Hosni et al. 2020). Although the data in EEG signals can be measured in the same way and with higher quality in magnetoencephalography (MEG)-based measurements, which is another method used to measure brain activities, the cost of this method and the difficulties in creating the measurement environment (the need for a magnetic field-isolated room) leave this method behind EEG (Nicolas-Alonso and Gomez-Gil 2012; Barnova et al. 2023). For these reasons, EEG signals are the most suitable and successful data source in this field.

In addition to these very important advantages, these biomarkers also have some disadvantages. There are some difficulties in processing these continuous-time signals. One of these difficulties is the elimination of artifacts that occur on the signal due to various factors (non-contact in the electrodes, disruptive electric and magnetic fields, problems in wireless sensor networks) from the raw signal while the signals are collected. These disruptive factors pose a major problem in obtaining meaningful information from the signal (Blinowska and Durka 2006). In conclusion, the advantages listed above for EEG signals far outweigh their disadvantages.

EEG is observed in all mammals. Primate EEG is the closest feature to human EEG. Although cat, dog, and rodent EEGs are similar to human EEG, they exhibit different spectral

TABLE 1 | Some publicly available EEG datasets and features.

Dataset	Reference	Features	Disorder	URL
University of Bonn	(Andrzejak et al. 2001)	• 1-Channel • 10 Subjects • Sampling rate: 173.61 Hz	• Epileptic Seizure	Link
CHB-MIT Scalp EEG Database	(Guttag n.d.)	• 18-Channel • 23 Subjects • Sampling Rate: 256 Hz	• Epileptic Seizure	Link
Siena Scalp EEG Database	(Detti n.d.)	• 29-Channel • 14 Subjects • Sampling Rate: 512 Hz	• Epileptic Seizure	Link
Sensorimotor Rhythm (SMR) based BCI Dataset	(Stieger et al. 2021)	• 62-Channel • 62 Subjects • Sampling Rate: 1000 Hz	• De-Identified	Link
GigaScience Database Multimodal Signal Dataset	(Jeong et al. 2020)	• 60-Channel • 25 Subjects • Sampling Rate: 2500 Hz	• Sensorimotor de−/activation • Spatial distribution	Link
EEG/FMRI Naturalistic Viewing Dataset	(Telesford et al. 2022)	• 64-Channel • 22 Subject • Sampling Rate: 5000 Hz	• De-Identified	Link
Melbourne NeuroVista Seizure Prediction Trial	(Karoly et al. n.d.)	• 16-Channel • 12 Subjects • Sampling Rate: 400 Hz	• Epilepsy	Link
Ear-EEG Recording for BCI of Motor Task	(Xiaoli et al. 2020)	• 122-Channel • 6 Subjects • Sampling Rate: 1000 Hz	• Motor Tasks	Link
Helsinki University Hospital Neonatal EEG Dataset	(Stevenson et al. n.d.)	• 19-Channel • 79 Subjects • Sampling Rate: 256 Hz	• Neonatal Seizure	Link
Pediatric Patients EEG with Epilepsy	(Cserpan et al. n.d.)	• 52-Channel • 30 Subjects • Sampling Rate: 2000 Hz	• Epilepsy	Link
Melbourne University AES/MathWorks/NIH Seizure Prediction	(Kuhlmann et al. n.d.)	• 16-Channel • 3 Subjects • Sampling Rate: 400 Hz	• Epilepsy	Link
Epileptic EEG Dataset	(Nasreddine n.d.)	• 21-Channel • 6 Subjects • 500 Hz	• Epilepsy	Link
EEG Recordings of Epilepsy Patients	(Andrzejak et al. 2012)	• 64-Channel • 5 Subjects • Sample Rate: 512 Hz	• Epilepsy	Link
Neurology and Sleep Centre Hauz Khas	(Swami et al. n.d.)	• 1-Channel • 10 Subjects • Sampling Rate: 200 Hz	• Epilepsy	Link
Multicenter Intracranial EEG Dataset	(Nejedly et al. 2020)	• 192-Channel • 39 Subjects • Sample Rate: 5000 Hz	• Epilepsy	Link

characteristics. In this study, only studies on EEG signals obtained from human subjects were examined.

2.2.1 | Publicly Available Datasets

While creating this study, we came across a few publicly available EEG datasets, and we have shared them in Table 1. EEG datasets are mostly not shared publicly due to privacy and confidentiality concerns.

2.3 | Decision Support- Systems and Artificial Intelligence

A clinical decision support system (CDSS) aims to meliorate healthcare by integrating clinical information, patient information, and other health information (Osheroff 2012). These systems provide patient-specific assessments and recommendations by matching individual personal characteristics with a clinical information base (Sim et al. 2001). In the context of EEG-based medical decision support, Figure 2 illustrates three key approaches: deriving insights from EEG signal features, classifying extracted features using ML, and applying DL methods directly to EEG signals. These approaches enable physicians to make more accurate and faster decisions.

The effectiveness of modern CDSS has been significantly enhanced by the integration of artificial intelligence techniques, particularly ML and DL. ML involves algorithms that define their own rules from data, allowing systems to interpret new situations by learning from past experiences. The performance of ML systems largely be conditional on the volume and quality of available data (Beam and Kohane 2018; Peiffer-Smadja et al. 2020). In healthcare, the increasing acceptance of electronic health recordings and associated devices has led to significant growth in available data, often referred to as "big data." ML methods excel at analyzing and interpreting this data, providing clinicians with valuable patient-specific evaluations or recommendations (Abràmoff et al. 2018).

While traditional ML-based EEG signal classification methods have shown promise, they face several challenges. EEG signals are susceptible to interference from biological events (e.g., heartbeat, eye blinking, and muscle movements) and electronic equipment, creating artifacts that complicate interpretation and classification (Rashid et al. 2020). Furthermore, EEG signals have very low signal-to-noise ratios and are nonstationary with time-dependent auxiliary variables. Due to this nature of EEG signals, preprocessing and feature extraction become quite difficult (Zhang et al. 2021). To address these issues, DL methods have been developed. Unlike traditional ML methods, DL techniques automatically learn high-level and hidden complex features from raw EEG data, eliminating the need for preprocessing and time-consuming feature extraction steps (Altaheri et al. 2023). Various DL methods have been applied to EEG signal analysis, including CNN, Recurrent Neural Networks (RNN), Long-Short-Term Memory (LSTM), Graph Neural Networks (GNN), Deep Neural Networks (DNN), Artificial Neural Networks (ANN), Multilayer Perceptron (MLP), 1D-CNN, Deep Transformer, Fully Connected Layers (FCL), Spiking Neural Networks (SNN), and CNN-based pretrained networks.

3 | Article Search and Selection Methods

In this study, the PRISMA 2020 guideline (Page et al. 2021) was used for the systematic review of ML or DL-based studies in which neurological and mental disorders are detected using EEG signals. Relevant studies were systematically searched from Scopus, Web of Science, Science Direct, PubMed, and IEEE databases, with the criteria of being published between 2013 and August 2024 as an initial condition.

Study selection criteria are established to determine whether a study should be included in this systematic review. There is no universal definition of quality criteria for primary studies, and each systematic literature review has its own task-specific criteria (Ebrahimighahnavieh et al. 2020). Studies that provide the following criteria were examined in this review:

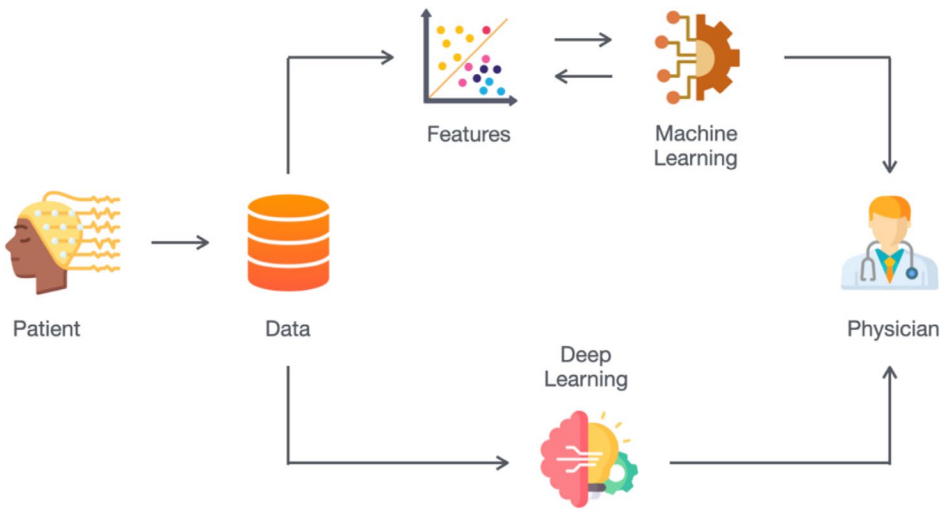

FIGURE 2 | Information pathways diagram for the clinical decision support system.

TABLE 2 | Inclusion/exclusion criteria list.

Inclusion criteria	Exclusion criteria
• Article published between 2013-August 2024	• Not using any AI methods
• Employ EEG signals to identify disorders	• Not in the English language
• Providing meaningful results	• Conference, book/book chapter, non-journal type studies
• Have full-text access	• Not provide any quantitative metric
• Presenting at least one of the specified metrics	• Review, systematic mapping or survey-type studies
• Published in Q1/Q2 indexed journals	• Being a different disease than the diseases sought
	• Those who do not meet any of the inclusion criteria

- Papers should employ EEG signals to identify neurological and mental health conditions and draw insightful findings for the diagnosis and treatment of these conditions.
- Implementation of at least one ML or DL method.
- Presentation of quantitative metrics (accuracy, F1 score, sensitivity, specificity, AUC).
- Full-text availability in English.
- Original research (not reviews, systematic mappings, or surveys).
- Studies other than those related to bipolar disorder (BD), stroke, Huntington's disease (HD), multiple sclerosis (MS), amyotrophic lateral sclerosis (ALS), Parkinson's disease (PD), obsessive compulsive disorder (OCD), bipolar depression (BD), depression, anhedonia, stress, anxiety, post-traumatic stress disorder (PTSD), major depressive disorder (MDD), attention-deficit/hyperactivity disorder (ADHD), schizophrenia, psychopathy, psychosis, focal cortical dysplasia (FCD), seizure, brain trauma (BT), brain injury (BI), Alzheimer's disease (AD), Lewy body disease (LBD) and autism spectrum disorder (ASD) were out of the scope of this research.

The summary features of these criteria are as shown in Table 2.

The initial keywords in the 'Title' section of the search were firstly chosen; ("Mental Disorder" OR "Mental Health" OR "Mental Disease" OR "Neurological Health" OR "Neurological Disease" OR "EEG" OR "Electroencephalograph" OR "EEG Signal" OR "EEG Signals") for an across-the-board search to avoid missing potentially relevant studies at all databases. Then with Boolean search string "AND," the search string associated with some specific illnesses in the abstract and keywords; Abstract-Keywords ("Bipolar Disorder" OR "Stroke" OR "Huntington's Disease" OR "Multiple Sclerosis" OR "Focal Cortical Dysplasia" OR "Seizure" OR "Traumatic Brain Injury" OR "Amyotrophic Lateral Sclerosis" OR "Parkinson's Disease" OR "Obsessive Compulsive Disorder" OR "Attention-Deficit/Hyperactivity Disorder" OR "Depression" OR "Bipolar Depression" OR "Bipolar Mania" OR "Anhedonia" OR "Stress" OR "Anxiety" OR "Post-Traumatic Stress Disorder" OR "Major Depressive Disorder" OR "Schizophrenia" OR "Psychopathy" OR "Psychosis" OR "Alzheimer" OR "Lewy Body Disease" OR "Autism Spectrum Disorder").

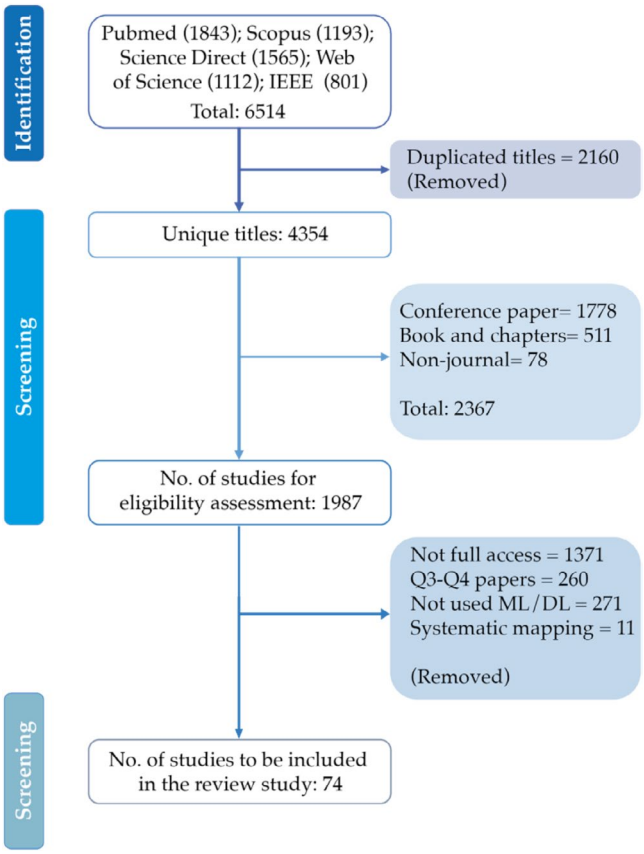

FIGURE 3 | Flowchart of the study selection process.

Figure 3 shows the article selection process applied according to this protocol. Following the PRISMA method, our initial search across all databases yielded 6514 studies. After removing 2160 duplicates, 4354 unique studies remained. Two collaborators independently reviewed all titles and abstracts, with a third collaborator resolving any disagreements. This process eliminated conferences, books, book chapters, and non-journal research items, reducing the count to 1987 studies. Further filtering excluded publications without open access, those not in Q1/Q2 indexed journals, studies not using ML or DL methods, and systematic mappings. This final screening resulted in 74 studies convenient for inclusion in our review.

4 | Results

4.1 | Main Findings

Our systematic review of studies published between 2013 and August 2024 revealed a significant trend in the application of AI techniques for the automated detection of neurological and mental health disorders using EEG signals. As illustrated in Figure 4, there has been a notable increase in the number of published articles meeting our inclusion criteria over the past 2 years, with a particularly sharp rise in 2024.

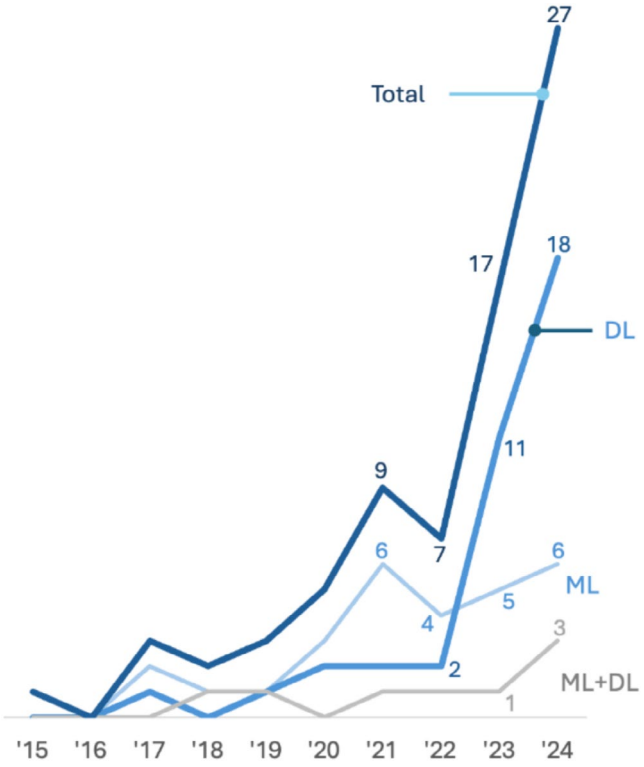

FIGURE 4 | Secular trend of reviewed studies, stratified by ML versus DL versus hybrid ML and DL.

This trend can be attributed to several factors: (i) advancements in AI technologies, particularly in Deep Learning (DL) methods; (ii) growing interest in non-invasive diagnostic tools for neurological and mental health disorders; (iii) improved computational resources enabling more complex analyses. The rise in DL methods is particularly evident in recent years, suggesting a shift in the field toward more sophisticated AI approaches. This trend likely reflects the ability of DL algorithms to automatically extract relevant features from raw EEG data, potentially offering improved performance over traditional ML methods that often require manual feature engineering.

Our review encompassed 74 studies utilizing a total of 49 distinct AI algorithms (26 ML, 22 DL, 1 hybrid). The distribution of studies across different neurological and mental health conditions is visualized in Figure 5. Epilepsy emerged as the most extensively studied disorder, with 32 eligible studies accounting for more than 40% of the total reviewed articles. This predominance likely reflects the clear manifestation of epileptic activity in EEG signals and the critical need for accurate seizure detection and prediction. The relatively high number of studies on depression and Alzheimer's Disease reflects the growing global burden of these conditions and the increasing recognition of EEG's potential as a diagnostic tool in these areas. The limited number of studies on conditions like seizure, stroke, and anxiety highlights areas where further research is needed. This gap presents opportunities for future studies to explore the application of

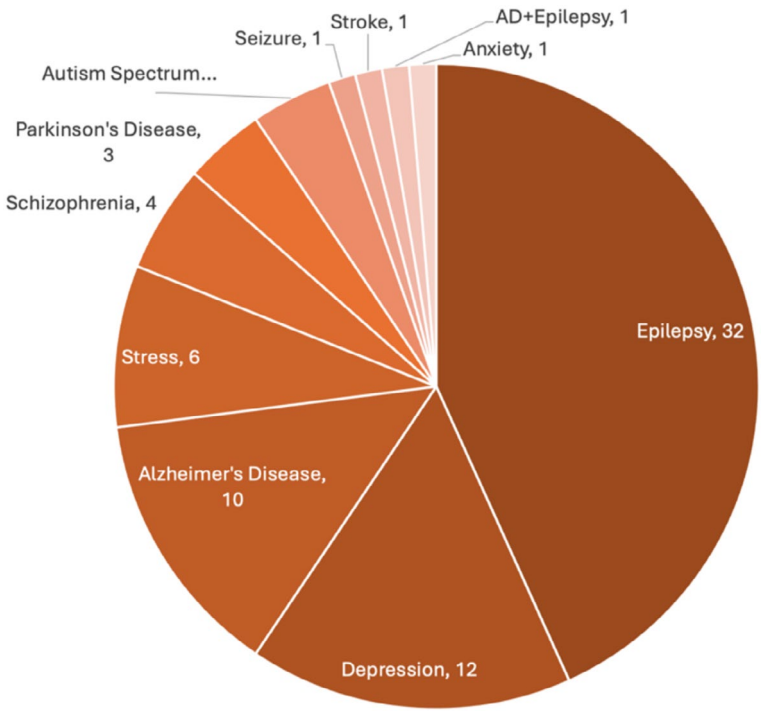

FIGURE 5 | Number of studies stratified by conditions according to diseases.

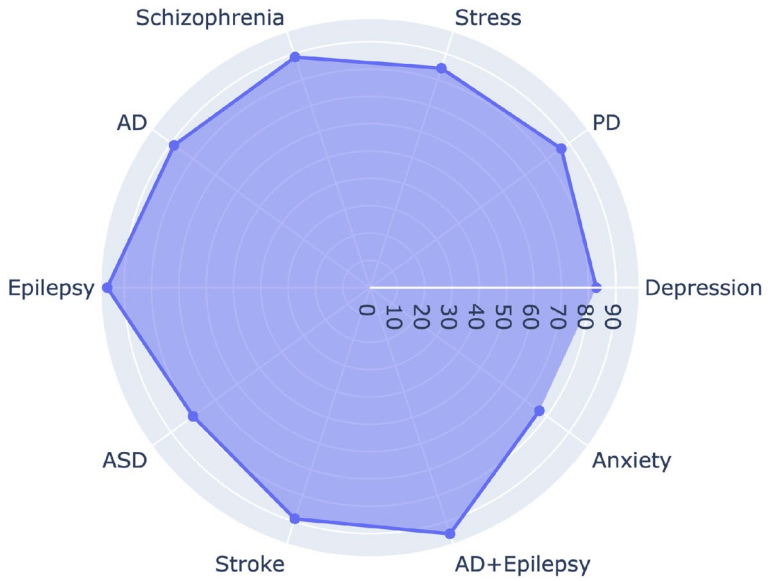

FIGURE 6 | Average values of the accuracy metric in all categories (in %).

FIGURE 7 | Average values of the sensitivity metric in all categories (in %).

AI techniques in EEG analysis for these under-represented conditions. Detailed information about each study, including methodologies, datasets, and performance metrics, is provided in Tables A1–A8 in Appendix A. Also, average results of different classifiers result on each disease are provided in Tables A9–A16 in Appendix B.

4.2 | Performance of the AI Models

To objectively compare the performance of AI models across different neurological and mental health conditions, we analyzed *five* key performance metrics: accuracy (ACC), sensitivity, specificity, AUC (area under the curve), and F1 score. Figures 6–10 illustrate these metrics for the 10 categories examined in this review.

ACC represents the ratio of correct predictions to the total number of samples, providing an overall measure of model performance. Sensitivity, also known as recall or true positive rate (TPR), indicates the model's ability to identify positive cases correctly. Specificity, or true negative rate (TNR), measures the model's ability to identify negative cases correctly. The AUC (area under the receiver operating characteristic (ROC) curve) quantifies the model's ability to distinguish between classes across various thresholds. The F1 score, in other words, the harmonic mean of precision and recall, provides a balanced measure of the model's performance, which is useful for imbalanced datasets (Naser and Alavi 2023).

Our analysis revealed that studies focusing on epilepsy, schizophrenia, and stroke demonstrated the highest overall performance using these metrics. However, it is crucial to

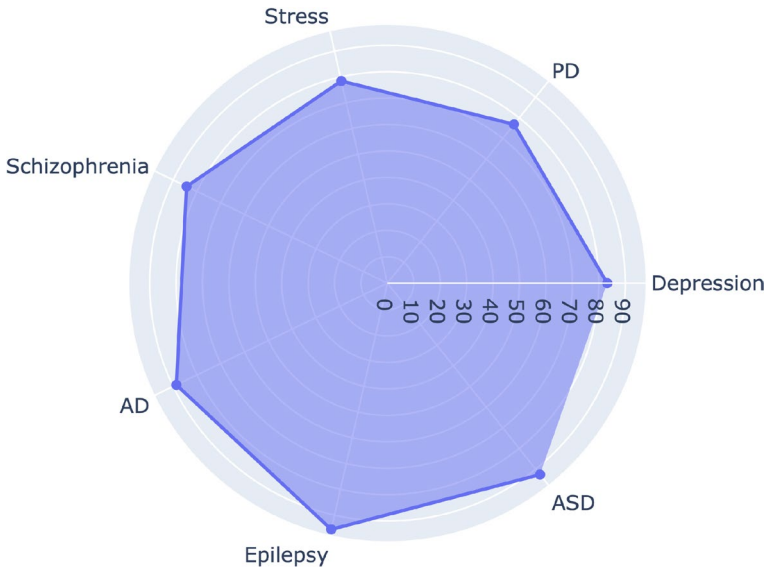

FIGURE 8 | Average values of the specificity metric in all categories (in %).

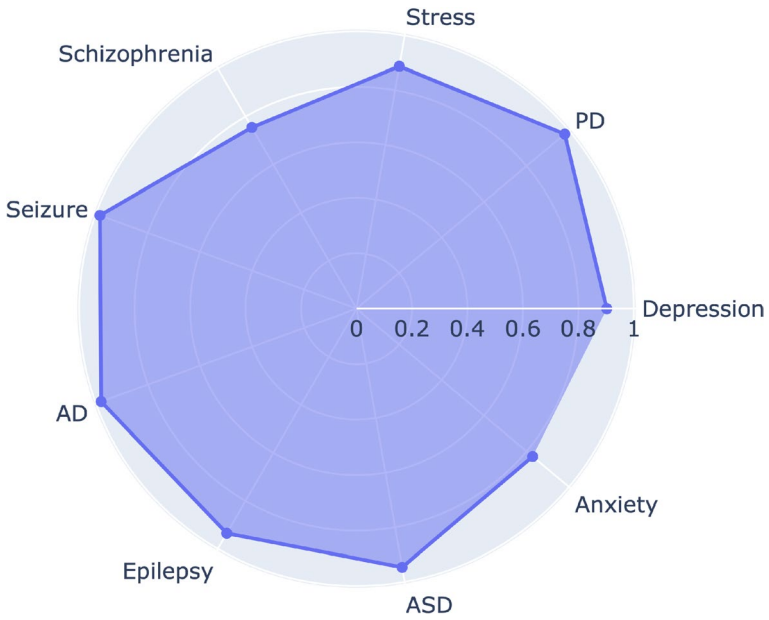

FIGURE 9 | Average values of the AUC metric in all categories (in %).

interpret these results cautiously, for conditions as they were conducted using smaller databases. The performance metrics for stress, schizophrenia, PD, and ASD may not represent general trends as the studies were performed using smaller databases. Similarly, the scarcity of studies on stroke, seizure, and anxiety underscores the need for more research in these areas to establish reliable performance benchmarks for EEG studies.

The following observations are made using the individual matrices based on Figures 6–10:

1. *Accuracy*: It may be noted from Figure 6 that the studies on epilepsy have obtained the highest accuracy values. The lowest average accuracy value was obtained for anxiety studies. Since studies based on epilepsy mostly performed seizure detection and reported high classification accuracy, as it is a binary classification. On the other hand, anxiety detection from EEG signals is much more difficult than epilepsy disease because there are no obvious amplitude and frequency differences, and there are sudden changes in the EEG signals with epilepsy disease. This situation leads to lower accuracy in the anxiety diagnosis.
2. *Sensitivity*: Figure 7 shows that epilepsy and schizophrenia studies showed high sensitivity, indicating strong performance in identifying true positive cases. Surprisingly, stress-related studies showed lower sensitivity despite having more studies than schizophrenia, suggesting potential challenges in detecting stress-related EEG patterns.
3. *Specificity*: Figure 8 indicates that epilepsy studies demonstrated the highest specificity, while stress and PD studies

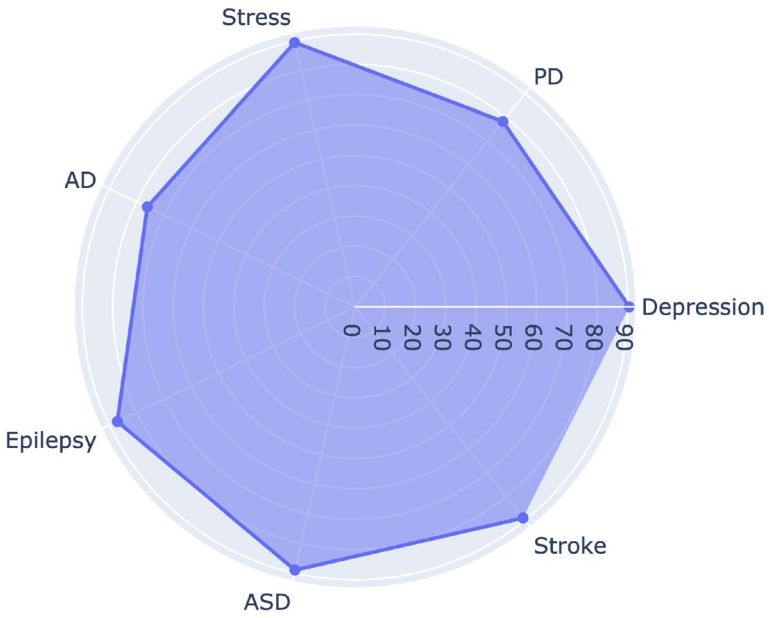

FIGURE 10 | Average values of the F1-score metric in all categories (in %).

showed the lowest. This suggests that while AI models are adept at ruling out epilepsy in non-epileptic individuals, they may struggle more with distinguishing stress or PD from other conditions or normal states.

4. *AUC*: Figure 9 represents that PD, seizure, and Alzheimer's disease (AD) studies achieved the best AUC scores, indicating good overall discriminative ability. Schizophrenia studies, however, showed the lowest AUC scores, suggesting potential difficulties in distinguishing schizophrenia from other conditions across different classification thresholds.
5. *F1 Score*: It may be noted from Figure 10 that studies on stress, ASD, stroke, and depression achieved high F1 scores, indicating a good balance between precision and recall. Conversely, AD and PD studies showed lower F1 scores, suggesting potential imbalances between precision and recall in these domains.

These performance variations across different disorders and metrics highlight the complexity of EEG-based diagnosis and the importance of choosing appropriate evaluation metrics based on the specific clinical context. The high performance in epilepsy detection may be attributed to the distinct EEG patterns associated with epileptic activity. The strong performance in schizophrenia studies, despite limited sample sizes, suggests promising avenues for EEG-based schizophrenia diagnosis; though more extensive studies are needed to confirm these findings.

The lower performance in stress detection, particularly in sensitivity, underscores the challenges in identifying stress-related EEG patterns, which may be more subtle or variable than those associated with other conditions. The mixed results for PD and AD, with high AUC but lower F1 scores, indicate good overall discriminative ability but potential issues with balancing false positives and false negatives.

4.3 | ML Versus DL Models

The sunburst diagram in Figure 11 visualizes the distribution of studies across various neurological and mental disorders, along with the AI techniques used. This comprehensive overview reveals the diversity of the approaches in the neurological and mental health field and highlights the predominance of certain methods in specific disease categories.

In our analysis, we observed distinct trends in the application of ML and DL methods across different disorders. Within ML techniques, support vector machines (SVM) emerged as the most frequently used algorithm. This popularity of SVM can be attributed to its high-dimensional data processing and its superior ability to find optimal decision boundaries in complex feature spaces. These features have a very important place in EEG signal analysis. In the domain of DL, convolutional neural networks (CNN) were predominant. The prevalence of CNNs is likely due to their ability to automatically learn hierarchical features from raw EEG data, capturing both spatial and temporal patterns effectively.

Figure 12 presents a radar graph comparing the accuracy of various traditional ML models across all application areas. Notably, Gradient Boosting Machine (GBM), Sparse Representation-Based Classification (SRC), and Takagi-Sugeno-Kang classifier (TSKC) methods demonstrated the highest accuracy among ML algorithms. These methods excelled in handling complex, non-linear relationships in data, which is particularly relevant for EEG signal analysis. In contrast, Classification Trees (CT), Decision Trees (DT), and Bagging methods showed relatively lower accuracy. This disparity might be due to the limitations of these simpler models in capturing the intricate patterns present in EEG data.

Figure 13 illustrates the accuracy of different DL algorithms across all application areas. One-dimensional CNN (1D-CNN), Graph Neural Networks (GNN), and Recurrent Neural Networks (RNN)

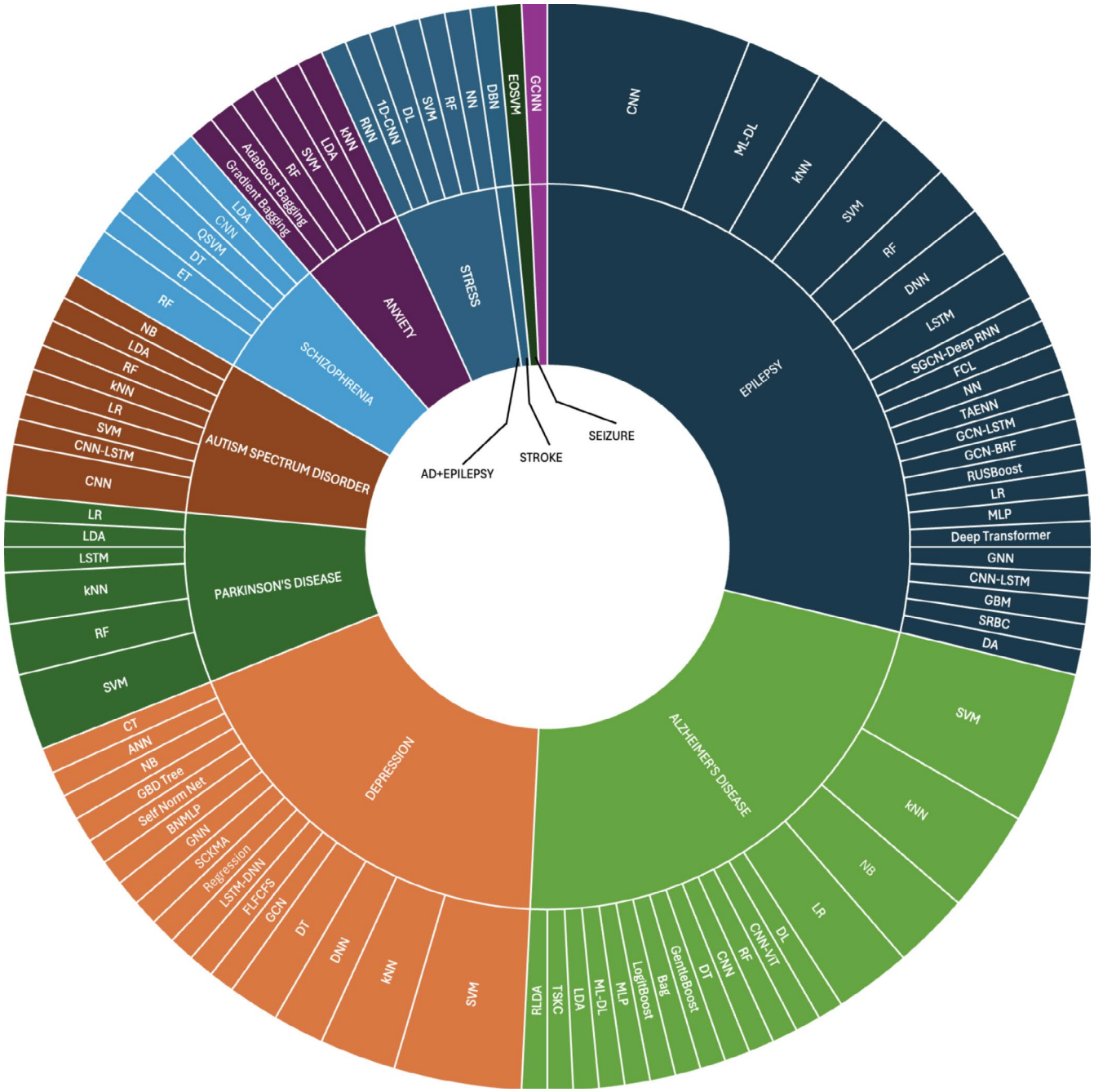

FIGURE 11 | Sunburst diagram of the studies on the automated detection of neurological and mental diseases using ML, DL, and hybrid techniques with EEG signals.

emerged as the top performers in terms of accuracy. The success of these models can be attributed to their ability to effectively process sequential data (RNN), capture spatial relationships (GNN), and extract relevant features from one-dimensional signals (1D-CNN). It is noteworthy that all DL algorithms achieved an accuracy of over 80%, underscoring the potential of deep learning approaches in EEG-based disorder detection.

Figure 14 provides the comparison of hybrid models that combine multiple ML and DL techniques. The hybrid model integrating DT, SVM, Random Forests (RF), Explainable Boosting Machines (XBM), k-Nearest Neighbors (kNN), and Artificial Neural Networks (ANN) demonstrated the highest accuracy among all models examined. This superior performance highlights the potential of ensemble methods in leveraging the strengths of diverse algorithms to achieve more robust and accurate predictions.

Finally, Figure 15 focuses on the accuracy of various DL models. Neural Network (NN) based algorithms consistently showed the highest accuracy values among DL models. This dominance of NN-based approaches underscores their effectiveness in processing and interpreting complex EEG data. The superior performance of DL models, particularly CNN and RNN variants, across various disorders, suggests a paradigm shift toward more sophisticated AI approaches in EEG analysis.

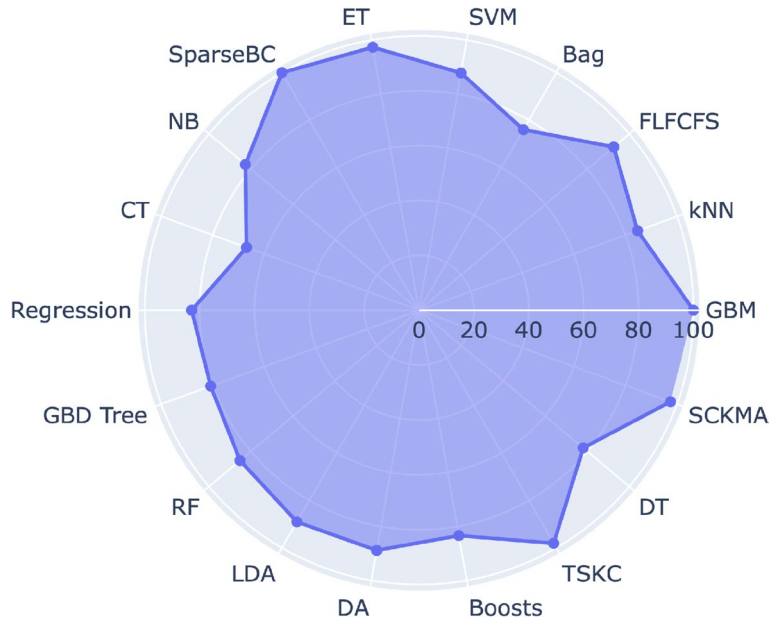

FIGURE 12 | Average values of the accuracy metric of traditional ML models across all application areas (in %).

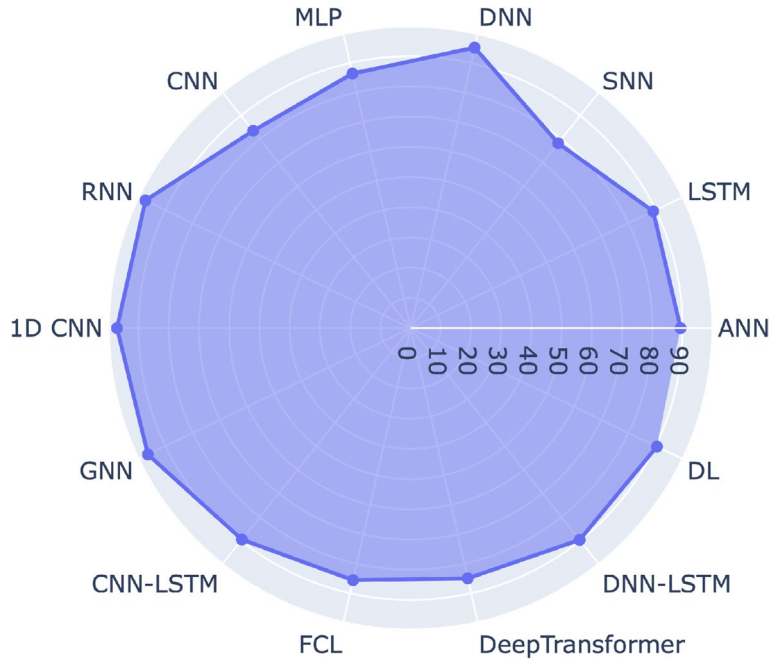

FIGURE 13 | Average values of the accuracy metric of DL models across all application areas (in %).

5 | Discussion

This systematic review provides an overview of the approaches used for detecting neurological and mental disorders using EEG signals, based on 74 scientific articles published between 2013 and August 2024. We examined several categories of disorders, with epilepsy, AD, and depression emerging as the most extensively researched areas.

Our study investigated traditional ML, DL, and hybrid (ML-DL) methods for diagnosing neurological and mental disorders. Notably, we found no studies meeting our inclusion criteria prior to 2015, suggesting a recent surge in this field. Figure 5 represents the number of studies conducted on ML, DL, and ML-DL techniques.

The analysis revealed a slight dominance of ML methods (26) over DL (22) and hybrid (1) approaches. This trend may be attributed to the limited feature data provided by EEG signals due to their low spectral properties (maximum frequency band range of 0.5–100 Hz (Niedermeyer and Lopes da Silva 2005)). However, DL methods have demonstrated clear superiority in detecting neurological and mental disorders, primarily due to their ability to extract features automatically, overcoming

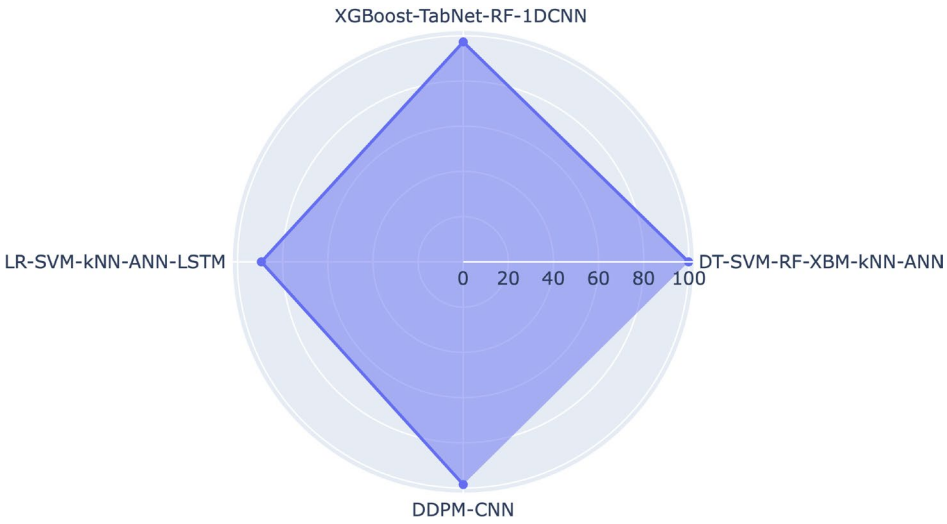

FIGURE 14 | Average values of the mean accuracy metric of ML-DL models across all application areas (in %).

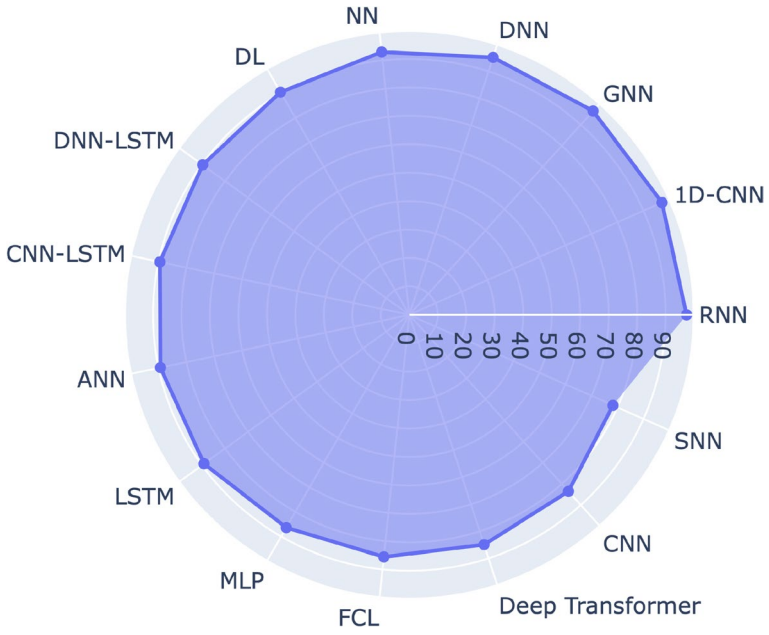

FIGURE 15 | Average values of the accuracy metric of DL models across all application areas (in %).

a significant limitation of ML and hybrid methods. Recent trends suggest a continued increase in the use of DL models in this field.

Several studies across various disorder categories demonstrated remarkable classification accuracy. Sharma et al. (Sharma et al. 2023) developed a wearable depression detection device using DL methods for smart healthcare services. Their model with STFT and the CNN-LSTM model achieved 99.9% classification accuracy. Aljalal et al. (2022) used DWT-based entropy features and achieved nearly 100% accuracy in distinguishing Parkinson's patients from healthy subjects across two datasets. Aksoy et al. (2024) proposed a quantum-based ML algorithm with PCA and QSVM and achieved 100% classification success in detecting schizophrenia. Khare and Acharya (2023) introduced the Adazd-Net model, which combines ML and DL methods for the automatic diagnosis of AD. They achieved 99.85% accuracy in AD diagnosis from EEG signals with 10-fold cross-validation. Sheykhivand et al. (2020) proposed a seizure detection method using EEG signals and sparse representation-based classification (SRC) theory. They achieved 100% accuracy using tests carried out on various scenarios. Sunaryono et al. (2022) employed discrete Fourier transform (DFT), DWT coupled with a gradient boosting classifier (GBM) classifier and reported 100% accuracy in epilepsy diagnosis. Islam et al. (2023) proposed a DL model for epilepsy diagnosis using noisy EEG signals, CWT, spectrogram, Wigner-Ville distributions, and CNN, and reported 100% accuracy. Zazzaro and Pavone (2022) classified features obtained through information gain, Pearson correlation filters, kNN classifier, and achieved 100% classification success for automatic detection of epilepsy. Tawhid et al. (Tawhid et al. 2021) used time-frequency spectrograms of EEG signals, a CNN model, and SVM to detect ASD. They reported an accuracy of 95.25% in the detection of ASD.

This research intersects neuroscience, psychology, biomedical engineering, and computer science, fostering collaborations that

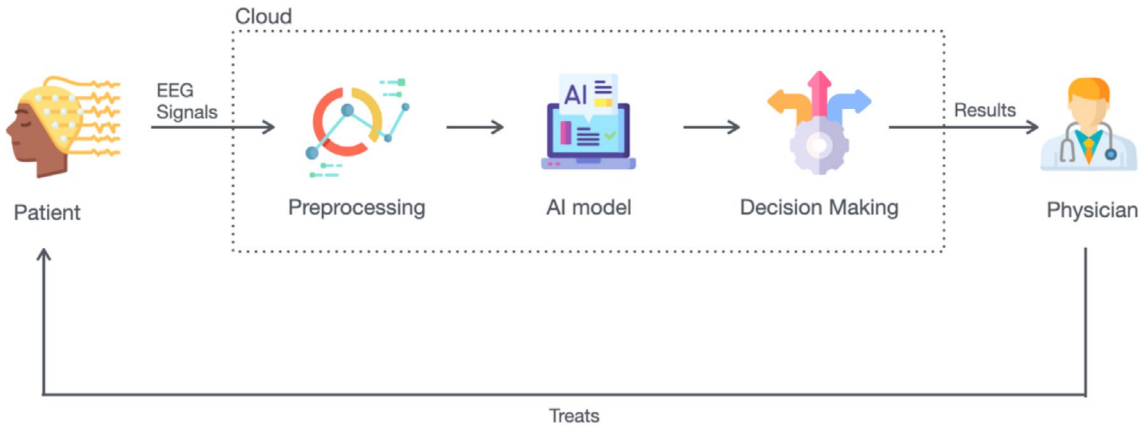

FIGURE 16 | A cloud-based CDSS system.

drive innovation across these fields. From a neuroscience perspective, the success of AI models in detecting disorders from EEG signals provides new insights into the neural correlates of various conditions. In psychology, these methods offer the potential for more objective, physiologically based markers of mental states. For biomedical engineering, this work promotes advancements in EEG technology and signal processing. Moreover, this interdisciplinary approach impacts medical education, potentially reshaping how future healthcare professionals are trained to interpret and utilize AI-assisted diagnostic tools.

In addition, with a cloud-based CDSS like in Figure 16 to be established globally in the future, it will be inevitable for the above-mentioned collaborations to work more efficiently and successfully. Such a system will provide great conveniences and solutions in the diagnosis, treatment, and tracking of neurological and mental diseases. It will be more possible to deliver such services to regions where telemedicine cannot reach.

5.1 | Limitations

This systematic review provides information about the application of AI techniques for EEG-based detection of neurological and mental disorders. The limitations of this study are listed below.

- As evident from Tables A1–A8, the studies included in this review utilized a diverse range of datasets, varying in size, participant demographics, and data collection protocols. The number of subjects across studies varies significantly, ranging from small-scale experiments to large cohort studies. Additionally, the electrode arrangements and EEG recording techniques differ between studies. This heterogeneity makes direct comparisons between studies challenging and may limit the generalizability of findings across different populations and clinical settings.
- The studies employed diverse preprocessing techniques and feature extraction methods, which can significantly impact the performance of AI models. The lack of standardization in these crucial steps makes it difficult to isolate the effects of the AI algorithms themselves from the effects of data preparation techniques.
- While accuracy is commonly reported across studies, there is a lack of consistency in reporting other crucial performance metrics such as sensitivity, specificity, F1 score, and AUC. This inconsistency hinders a comprehensive evaluation of model performance, particularly in cases where class imbalance may be present. A more standardized approach to reporting a full suite of performance metrics would facilitate better cross-study comparisons.
- Most of the reviewed studies are cross-sectional, providing a snapshot of EEG-based disorder detection at a single time point. The scarcity of longitudinal studies limits our understanding of how AI models perform over time and across different stages of disease progression.
- While the performance of AI models is often reported, there is often limited discussion on the interpretability of these models, which is crucial for clinical adoption and trust in AI-assisted diagnosis.

5.2 | Future Studies

Mental disorders have been a persistent global issue throughout human history. Research has established strong links between these disorders and various factors, including genetic predisposition, hormonal imbalances, social environment, and chronic diseases (Walker et al. 2015). Despite significant progress in identifying many mental disorders, there remain substantial gaps in our understanding and treatment capabilities, both for known and yet-to-be-discovered conditions. We propose that a crucial step in addressing these gaps is the further development of CDSSs. The creation of a global system for continuous data analysis and prediction of neurological and mental illnesses would represent a significant advancement in this field. This is particularly important given the limited reach of telemedicine in many parts of the world. The implementation of such systems, along with internet and phone-based support systems and mobile applications for mental health, could potentially lead to a marked reduction in the prevalence of these disorders.

A significant limitation in current research is the reliance on non-public datasets. The majority of studies examined in this review were conducted using private datasets. The scarcity of

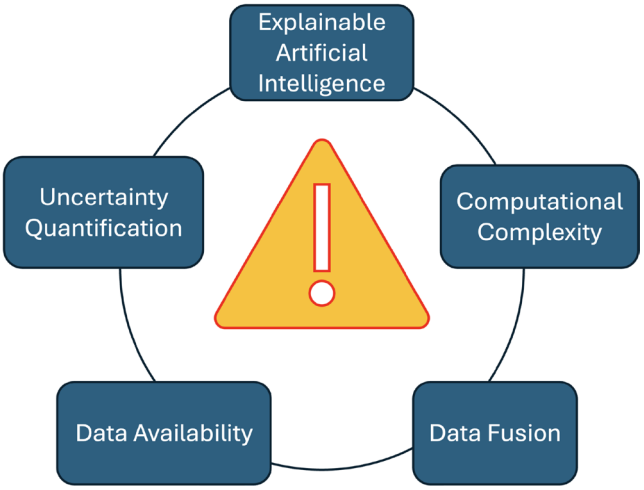

FIGURE 17 | Illustration of future directions.

publicly available mental health datasets, primarily due to privacy and confidentiality concerns, has restricted the scope and number of studies in this field. This limitation is evident by the number of articles published. To enhance our understanding of neurological and mental diseases, there is a pressing need for more publicly accessible datasets.

DL-based studies on EEG signal analysis for neurological and mental disorder detection have shown promising results and demonstrated high efficiency (Malviya and Mal 2022; Sun et al. 2021; Tasci et al. 2023; Shah et al. 2023; Rafiei et al. 2022; Alves et al. 2022; Sarkar et al. 2022). This efficiency underscores the need for developing new models in this field. The potential for systems that can make rapid, accessible, and transparent decisions could significantly reduce the impact of these diseases.

We also envision the establishment of a global mental health system. This system would integrate CDSS and a shared dataset pool, enabling quick and cost-effective dissemination of diagnostic and treatment services worldwide. The development of AI-based systems integrated with these platforms could lead to mutual advancements in both medical practice and artificial intelligence research.

Figure 17 shows a visual that includes the most important fundamental issues of future directions that we noticed throughout this study.

Recently, AI methods are becoming more popular and widespread due to their ease of use and the successful results they provide. As with many other state-of-the-art models, the biggest problem of AI is its lack of transparency and interpretability (Dosilovic et al. 2018). This deficiency creates a major disadvantage in areas where errors are unacceptable, such as autonomous driving, military, and healthcare. This situation has led to the emergence of the concept of explainable artificial intelligence (XAI) in the field of AI. XAI was essentially created to improve the interpretability of ML and to produce solutions like LIME (Local Interpretable Model-Agnostic Explanations) (Ribeiro et al. 2016), SHAP (SHapley Additive exPlanations) (Lundberg and Lee 2017), and GradCam (Gradient-weighted Class Activation Mapping) (Selvaraju et al. 2020) to increase trust in these systems (Xiong, Li et al. 2024). With the prevalence of neurological and mental health studies that take this issue into account, like studies (Mishra et al. 2021; Ammar and Shaban-Nejad 2020; Jaber et al. 2022) eliminating the deficiencies in AI-based studies and increasing trust in AI will be inevitable.

In addition, improvement in the detection can be achieved by measuring the amount of uncertainties caused by noise in EEG signals. In clinical artificial intelligence applications, the process of measuring uncertainty reduces misclassifications, improves model accuracy, and identifies uncertain cases, while increasing the reliability and safety of the model used and the trust between clinical operators (Seoni et al. 2023). Bayesian networks and fuzzy methods are used to make precise predictions during uncertainty. Uncertainty quantification (UQ) helps to quantify and minimize the uncertainty due to models or data (Flügge et al. 2019).

In this review, we observed that the majority of the studies relied on EEG signals alone. This singular focus highlights a critical area for future research—the integration of additional biomarkers alongside EEG data. We believe that data fusion, which incorporates multiple biomarkers, such as neuroimaging data (e.g., fMRI, PET), genetic markers, or even behavioral and cognitive assessments along with EEG, could substantially enhance the success of neurological and mental disorder detection and will improve the uncertainty estimation of the model.

6 | Conclusion

This systematic review analyzed 74 Q1/Q2 studies published between 2013 and August 2024 on the automated detection of neurological and mental health disorders using EEG signals and AI techniques. The analysis revealed a significant focus on epilepsy, Alzheimer's disease, and depression detection studies. The SVM and CNN are widely used in ML and DL studies, respectively, to detect these various neurological and mental health disorders. A notable trend toward DL-based studies was observed, with these methods often outperforming traditional approaches in accuracy and feature extraction.

While many studies reported high classification accuracies, often exceeding 99%, it is important to note that most were conducted in controlled research settings. Future research should focus on larger, more diverse datasets, standardization of techniques, and clinical validation in a real-world environment. The integration of AI-based EEG analysis in healthcare shows promise for enhancing diagnosis and understanding of these disorders, potentially leading to earlier interventions and improved patient outcomes. However, these methods should be viewed as complementary tools to existing clinical practices rather than replacements.

Lastly, the advancement of this field will depend on the integration of XAI approaches, multi-modal data fusion

techniques, and uncertainty quantification methods. These components not only improve AI models' reliability and interpretability, but they also foster crucial trust among medical professionals.

Author Contributions

Hakan Uyanik: investigation (equal), methodology (equal), visualization (equal), writing – original draft (equal). **Abdulkadir Sengur:** methodology (equal), writing – original draft (equal). **Massimo Salvi:** methodology (equal), validation (equal), writing – review and editing (equal). **Ru-San Tan:** methodology (equal), supervision (equal), validation (equal), writing – review and editing (equal). **Jen Hong Tan:** validation (equal), visualization (equal). **U. Rajendra Acharya:** methodology (equal), supervision (equal), validation (equal), writing – review and editing (equal).

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The authors have nothing to report.

Related WIREs Articles

A survey of autonomous monitoring systems in mental health

References

Abbasi, M. U., A. Rashad, A. Basalamah, and M. Tariq. 2019. "Detection of Epilepsy Seizures in Neo-Natal EEG Using LSTM Architecture." *IEEE Access* 7: 179074–179085. https://doi.org/10.1109/ACCESS.2019.2959234.

Abràmoff, M. D., P. T. Lavin, M. Birch, N. Shah, and J. C. Folk. 2018. "Pivotal Trial of an Autonomous AI-Based Diagnostic System for Detection of Diabetic Retinopathy in Primary Care Offices." *npj Digital Medicine* 1, no. 1: 39. https://doi.org/10.1038/s41746-018-0040-6.

Ajith, M., D. M. Aycock, E. B. Tone, et al. 2024. "A Deep Learning Approach for Mental Health Quality Prediction Using Functional Network Connectivity and Assessment Data." *Brain Imaging and Behavior* 18, no. 3: 630–645. https://doi.org/10.1007/s11682-024-00857-y.

Aksoy, G., G. Cattan, S. Chakraborty, and M. Karabatak. 2024. "Quantum Machine-Based Decision Support System for the Detection of Schizophrenia From EEG Records." *Journal of Medical Systems* 48, no. 1: 29. https://doi.org/10.1007/s10916-024-02048-0.

Al Banna, M. H., T. Ghosh, M. J. Al Nahian, M. S. Kaiser, M. Mahmud, and K. A. Taher. 2023. "A Hybrid Deep Learning Model to Predict the Impact of COVID-19 on Mental Health From Social Media Big Data." *IEEE Access* 11: 77009–77022. https://doi.org/10.1109/ACCESS.2023.3293857.

Aldayel, M., and A. Al-Nafjan. 2024. "A Comprehensive Exploration of Machine Learning Techniques for EEG-Based Anxiety Detection." *PeerJ Computer Science* 10: e1829. https://doi.org/10.7717/peerj-cs.1829.

Aljalal, M., S. A. Aldosari, M. Molinas, K. AlSharabi, and F. A. Alturki. 2022. "Detection of Parkinson's Disease From EEG Signals Using Discrete Wavelet Transform, Different Entropy Measures, and Machine Learning Techniques." *Scientific Reports* 12, no. 1: 22547. https://doi.org/10.1038/s41598-022-26644-7.

Alonso, J., Z. Liu, S. Evans-Lacko, et al. 2018. "Treatment Gap for Anxiety Disorders is Global: Results of the World Mental Health Surveys in 21 Countries." *Depression and Anxiety* 35, no. 3: 195–208. https://doi.org/10.1002/da.22711.

Al-Qazzaz, N. K., A. A. Aldoori, A. K. Buniya, S. H. B. M. Ali, and S. A. Ahmad. 2024. "Transfer Learning and Hybrid Deep Convolutional Neural Networks Models for Autism Spectrum Disorder Classification From EEG Signals." *IEEE Access* 12: 64510–64530. https://doi.org/10.1109/ACCESS.2024.3396869.

Altaheri, H., G. Muhammad, M. Alsulaiman, et al. 2023. "Deep Learning Techniques for Classification of Electroencephalogram (EEG) Motor Imagery (MI) Signals: A Review." *Neural Computing and Applications* 35, no. 20: 14681–14722. https://doi.org/10.1007/s00521-021-06352-5.

Alves, C. L., A. M. Pineda, K. Roster, C. Thielemann, and F. A. Rodrigues. 2022. "EEG Functional Connectivity and Deep Learning for Automatic Diagnosis of Brain Disorders: Alzheimer's Disease and Schizophrenia." *Journal of Physics: Complexity* 3, no. 2: 025001. https://doi.org/10.1088/2632-072X/ac5f8d.

Ammar, N., and A. Shaban-Nejad. 2020. "Explainable Artificial Intelligence Recommendation System by Leveraging the Semantics of Adverse Childhood Experiences: Proof-Of-Concept Prototype Development." *JMIR Medical Informatics* 8, no. 11: e18752. https://doi.org/10.2196/18752.

Andrzejak, R. G., K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger. 2001. "Indications of Nonlinear Deterministic and Finite-Dimensional Structures in Time Series of Brain Electrical Activity: Dependence on Recording Region and Brain State." *Physical Review E* 64, no. 6: 061907. https://doi.org/10.1103/PhysRevE.64.061907.

Andrzejak, R. G., K. Schindler, and C. Rummel. 2012. "Nonrandomness, Nonlinear Dependence, and Nonstationarity of Electroencephalographic Recordings From Epilepsy Patients." *Physical Review E* 86, no. 4: 046206. https://doi.org/10.1103/PhysRevE.86.046206.

Astle, D. E., and S. Fletcher-Watson. 2020. "Beyond the Core-Deficit Hypothesis in Developmental Disorders." *Current Directions in Psychological Science* 29, no. 5: 431–437. https://doi.org/10.1177/0963721420925518.

Awais, M., S. B. Belhaouari, and K. Kassoul. 2024. "Graphical Insight: Revolutionizing Seizure Detection With EEG Representation." *Biomedicine* 12, no. 6: 1283. https://doi.org/10.3390/biomedicines12061283.

Barnova, K., M. Mikolasova, R. V. Kahankova, et al. 2023. "Implementation of Artificial Intelligence and Machine Learning-Based Methods in Brain–Computer Interaction." *Computers in Biology and Medicine* 163: 107135. https://doi.org/10.1016/j.compbiomed.2023.107135.

Barros, C., B. Roach, J. M. Ford, A. P. Pinheiro, and C. A. Silva. 2022. "From Sound Perception to Automatic Detection of Schizophrenia: An EEG-Based Deep Learning Approach." *Frontiers in Psychiatry* 12: 813460. https://doi.org/10.3389/fpsyt.2021.813460.

Beam, A. L., and I. S. Kohane. 2018. "Big Data and Machine Learning in Health Care." *JAMA* 319, no. 13: 1317. https://doi.org/10.1001/jama.2017.18391.

Bell, C., N. Tesli, T. P. Gurholt, et al. 2022. "Associations Between Amygdala Nuclei Volumes, Psychosis, Psychopathy, and Violent Offending." *Psychiatry Research: Neuroimaging* 319: 111416. https://doi.org/10.1016/j.pscychresns.2021.111416.

Berger, I. 2011. "Diagnosis of Attention Deficit Hyperactivity Disorder: Much Ado About Something." *Israel Medical Association Journal* 13, no. 9: 571–574.

Blinowska, K., and P. Durka. 2006. "Electroencephalography (EEG)." In *Wiley Encyclopedia of Biomedical Engineering*. Wiley. https://doi.org/10.1002/9780471740360.ebs0418.

Blumcke, I., R. Spreafico, G. Haaker, et al. 2017. "Histopathological Findings in Brain Tissue Obtained During Epilepsy Surgery." *New England Journal of Medicine* 377, no. 17: 1648–1656. https://doi.org/10.1056/NEJMoa1703784.

Bruno, E., P. F. Viana, M. R. Sperling, and M. P. Richardson. 2020. "Seizure Detection at Home: Do Devices on the Market Match the Needs of People Living With Epilepsy and Their Caregivers?" *Epilepsia* 61, no. S1: S11–S24. https://doi.org/10.1111/epi.16521.

Cai, H., J. Han, Y. Chen, et al. 2018. "A Pervasive Approach to EEG-Based Depression Detection." *Complexity* 2018: 1–13. https://doi.org/10.1155/2018/5238028.

Cao, Z., A. R. John, H. T. Chen, et al. 2021. "Identification of EEG Dynamics During Freezing of Gait and Voluntary Stopping in Patients With Parkinson's Disease." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 29: 1774–1783. https://doi.org/10.1109/TNSRE.2021.3107106.

Chai, M., and L. Ba. 2021. "Application of EEG Signal Recognition Method Based on Duffing Equation in Psychological Stress Analysis." *Advances in Mathematical Physics* 2021: 1–10. https://doi.org/10.1155/2021/1454547.

Chaiyakunapruk, N., H. Y. Chong, S. L. Teoh, D. B.-C. Wu, S. Kotirum, and C.-F. Chiou. 2016. "Global Economic Burden of Schizophrenia: A Systematic Review." *Neuropsychiatric Disease and Treatment* 12: 357–373. https://doi.org/10.2147/NDT.S96649.

Chan, J. K. N., C. H. Y. Tong, C. S. M. Wong, E. Y. H. Chen, and W. C. Chang. 2022. "Life Expectancy and Years of Potential Life Lost in Bipolar Disorder: Systematic Review and Meta-Analysis." *British Journal of Psychiatry* 221, no. 3: 567–576. https://doi.org/10.1192/bjp.2022.19.

Chellappa, S. L., and D. Aeschbach. 2022. "Sleep and Anxiety: From Mechanisms to Interventions." *Sleep Medicine Reviews* 61: 101583. https://doi.org/10.1016/j.smrv.2021.101583.

Chen, W., Y. Wang, Y. Ren, et al. 2023. "An Automated Detection of Epileptic Seizures EEG Using CNN Classifier Based on Feature Fusion With High Accuracy." *BMC Medical Informatics and Decision Making* 23, no. 1: 96. https://doi.org/10.1186/s12911-023-02180-w.

Chen, Z., G. Lu, Z. Xie, and W. Shang. 2020. "A Unified Framework and Method for EEG-Based Early Epileptic Seizure Detection and Epilepsy Diagnosis." *IEEE Access* 8: 20080–20092. https://doi.org/10.1109/ACCESS.2020.2969055.

Chu, K. T., W. C. Lei, M. H. Wu, et al. 2023. "A Holo-Spectral EEG Analysis Provides an Early Detection of Cognitive Decline and Predicts the Progression to Alzheimer's Disease." *Frontiers in Aging Neuroscience* 15: 1–21. https://doi.org/10.3389/fnagi.2023.1195424.

Chung, K.-H., Y.-S. Chang, W.-T. Yen, L. Lin, and S. Abimannan. 2024. "Depression Assessment Using Integrated Multi-Featured EEG Bands Deep Neural Network Models: Leveraging Ensemble Learning Techniques." *Computational and Structural Biotechnology Journal* 23: 1450–1468. https://doi.org/10.1016/j.csbj.2024.03.022.

Cohen, S., D. Janicki-Deverts, and G. E. Miller. 2007. "Psychological Stress and Disease." *JAMA* 298, no. 14: 1685. https://doi.org/10.1001/jama.298.14.1685.

Cserpan, D., E. Boran, R. Rosch, S. Pietro Lo Biundo, G. Ramantani, and J. Sarnthein. n.d. Dataset of EEG Recordings of Pediatric Patients With Epilepsy Based on the 10-20 System Accessed September 3, 2024. https://openneuro.org/datasets/ds003555/versions/1.0.0/download.

Das, A. K., and R. Naskar. 2024. "A Deep Learning Model for Depression Detection Based on MFCC and CNN Generated Spectrogram Features." *Biomedical Signal Processing and Control* 90: 105898. https://doi.org/10.1016/j.bspc.2023.105898.

Detti, P. n.d. Siena Scalp EEG Database Accessed September 2, 2024. https://physionet.org/content/siena-scalp-eeg/1.0.0/.

Dogan, S., P. D. Barua, M. Baygin, et al. 2024. "Lattice 123 Pattern for Automated Alzheimer's Detection Using EEG Signal." *Cognitive Neurodynamics* 18: 2503–2519. https://doi.org/10.1007/s11571-024-10104-1.

Dosilovic, F. K., M. Brcic, and N. Hlupic. 2018. "Explainable Artificial Intelligence: A Survey." In *2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, 0210–0215. IEEE. https://doi.org/10.23919/MIPRO.2018.8400040.

Ebrahimighahnavieh, M. A., S. Luo, and R. Chiong. 2020. "Deep Learning to Detect Alzheimer's Disease From Neuroimaging: A Systematic Literature Review." *Computer Methods and Programs in Biomedicine* 187: 105242. https://doi.org/10.1016/j.cmpb.2019.105242.

Esmaeilpour, A., S. S. Tabarestani, and A. Niazi. 2024. "Deep Learning-Based Seizure Prediction Using EEG Signals: A Comparative Analysis of Classification Methods on the CHB-MIT Dataset." *Engineering Reports* 6: 1–9. https://doi.org/10.1002/eng2.12918.

Fan, M., A. C. Yang, J. L. Fuh, and C. A. Chou. 2018. "Topological Pattern Recognition of Severe Alzheimer's Disease via Regularized Supervised Learning of EEG Complexity." *Frontiers in Neuroscience* 12, no. OCT: 685. https://doi.org/10.3389/fnins.2018.00685.

Fava, M., and K. S. Kendler. 2000. "Major Depressive Disorder." *Neuron* 28, no. 2: 335–341. https://doi.org/10.1016/S0896-6273(00)00112-4.

Feigin, V. L., T. Vos, E. Nichols, et al. 2020. "The Global Burden of Neurological Disorders: Translating Evidence Into Policy." *Lancet Neurology* 19, no. 3: 255–265. https://doi.org/10.1016/S1474-4422(19)30411-9.

Feigin, V. L., and M. O. Owolabi. 2023. "Pragmatic Solutions to Reduce the Global Burden of Stroke: A World Stroke Organization–Lancet Neurology Commission." *Lancet Neurology* 22, no. 12: 1160–1206. https://doi.org/10.1016/S1474-4422(23)00277-6.

Fisher, K. A., T. J. Torrico, and M. Hany. 2024. "Antisocial Personality Disorder."

Flügge, S., S. Zimmer, and U. Petersohn. 2019. "Knowledge Representation and Diagnostic Inference Using Bayesian Networks in the Medical Discourse."

Ford, H. 2020. "Clinical Presentation and Diagnosis of Multiple Sclerosis." *Clinical Medicine* 20, no. 4: 380–383. https://doi.org/10.7861/clinmed.2020-0292.

Garg, S., U. P. Shukla, and L. R. Cenkeramaddi. 2023. "Detection of Depression Using Weighted Spectral Graph Clustering With EEG Biomarkers." *IEEE Access* 11: 57880–57894. https://doi.org/10.1109/ACCESS.2023.3281453.

Garip, Z., E. Ekinci, K. Serbest, and S. Eken. 2024. "Chaotic Marine Predator Optimization Algorithm for Feature Selection in Schizophrenia Classification Using EEG Signals." *Cluster Computing* 27: 11277–11297. https://doi.org/10.1007/s10586-024-04511-6.

Global Health Data Exchange. n.d. GBD Results Tool Accessed September 13, 2024. https://vizhub.healthdata.org/gbd-results?params=gbd-api-2019-permalink/716f37e05d94046d6a06c1194a8eb0c9.

Global Health Data Exchange (GHDx). n.d. Institute of Health Metrics and Evaluation (IHME) Accessed September 13, 2024. http://ghdx.healthdata.org/gbd-results-tool?params=gbd-api-2019-permalink/27a7644e8ad28e739382d31e77589dd7.

Global Health Data Exchange (GHDx). n.d.-a. Institute of Health Metrics and Evaluation Accessed September 13, 2024. https://vizhub.healthdata.org/gbd-results/.

Gómez, C., P. Arbeláez, M. Navarrete, C. Alvarado-Rojas, M. Le Van Quyen, and M. Valderrama. 2020. "Automatic Seizure Detection Based on Imaged-EEG Signals Through Fully Convolutional Networks."

Scientific Reports 10, no. 1: 21833. https://doi.org/10.1038/s41598-020-78784-3.

Grande, I., M. Berk, B. Birmaher, and E. Vieta. 2016. "Bipolar Disorder." *Lancet* 387, no. 10027: 1561–1572. https://doi.org/10.1016/S0140-6736(15)00241-X.

Guttag, J. n.d. CHB-MIT Scalp EEG Database Accessed September 2, 2024. https://physionet.org/content/chbmit/1.0.0/.

Hardiman, O., A. Al-Chalabi, A. Chio, et al. 2017. "Amyotrophic Lateral Sclerosis." *Nature Reviews. Disease Primers* 3, no. 1: 17071. https://doi.org/10.1038/nrdp.2017.71.

Harrison, G., K. Hopper, T. Craig, et al. 2001. "Recovery from Psychotic Illness: A 15- and 25-Year International Follow-Up Study." *British Journal of Psychiatry* 178, no. 6: 506–517. https://doi.org/10.1192/bjp.178.6.506.

Harshini, R. P., and R. Thangarajan. 2024. "A Review of Alzheimer's Disease Identification by Machine Learning." In *Reliability Engineering for Industrial Processes*, 203–211. Springer. https://doi.org/10.1007/978-3-031-55048-5_14.

Hosni, S. M., S. B. Borgheai, J. McLinden, and Y. Shahriari. 2020. "An fNIRS-Based Motor Imagery BCI for ALS: A Subject-Specific Data-Driven Approach." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 28, no. 12: 3063–3073 Dec. 2020. https://doi.org/10.1109/TNSRE.2020.3038717.

n.d. "Mental Disorders." Accessed August 6, 2024. https://www.who.int/news-room/fact-sheets/detail/mental-disorders.

Institute of Health Metrics and Evaluation. n.d. "Global Health Data Exchange (GHDx)." Accessed May 14, 2024. https://vizhub.healthdata.org/gbd-results/.

Islam, T., M. Basak, R. Islam, and A. D. Roy. 2023. "Investigating Population-Specific Epilepsy Detection From Noisy EEG Signals Using Deep-Learning Models." *Heliyon* 9, no. 12: e22208. https://doi.org/10.1016/j.heliyon.2023.e22208.

Jaber, D., H. Hajj, F. Maalouf, and W. El-Hajj. 2022. "Medically-Oriented Design for Explainable AI for Stress Prediction From Physiological Measurements." *BMC Medical Informatics and Decision Making* 22, no. 1: 38. https://doi.org/10.1186/s12911-022-01772-2.

Jaeschke, K., F. Hanna, S. Ali, N. Chowdhary, T. Dua, and F. Charlson. 2021. "Global Estimates of Service Coverage for Severe Mental Disorders: Findings From the WHO Mental Health Atlas 2017." *Global Mental Health* 8: e27. https://doi.org/10.1017/gmh.2021.19.

Jasphin Jeni Sharmila, P., and T. S. Shiny Angel. 2024. "Optimized Machine Learning Model for Alzheimer and Epilepsy Detection From EEG Signals." *Automatika* 65, no. 2: 597–608. https://doi.org/10.1080/00051144.2023.2297481.

Jemal, I., L. Abou-Abbas, K. Henni, A. Mitiche, and N. Mezghani. 2024. "Domain Adaptation for EEG-Based, Cross-Subject Epileptic Seizure Prediction." *Frontiers in Neuroinformatics* 18: 1303380. https://doi.org/10.3389/fninf.2024.1303380.

Jeong, J.-H., J. H. Cho, K. H. Shim, et al. 2020. "Multimodal Signal Dataset for 11 Intuitive Movement Tasks from Single Upper Extremity During Multiple Recording Sessions." *GigaScience* 9, no. 10: 1–15. https://doi.org/10.1093/gigascience/giaa098.

Jibon, F. A., A. R. Jamil Chowdhury, M. H. Miraz, et al. 2024. "Sequential Graph Convolutional Network and DeepRNN Based Hybrid Framework for Epileptic Seizure Detection From EEG Signal." *Digital Health* 10: 1–23. https://doi.org/10.1177/20552076241249874.

Johanson, M., O. Vaurio, J. Tiihonen, and M. Lähteenvuo. 2020. "A Systematic Literature Review of Neuroimaging of Psychopathic Traits." *Frontiers in Psychiatry* 10: 1027. https://doi.org/10.3389/fpsyt.2019.01027.

Kalra, S. 1996. "Lewy Body Disease and Dementia." *Archives of Internal Medicine* 156, no. 5: 487. https://doi.org/10.1001/archinte.1996.00440050031004.

Kamakshi, K., and A. Rengaraj. 2024. "Early Detection of Stress and Anxiety Based Seizures in Position Data Augmented EEG Signal Using Hybrid Deep Learning Algorithms." *IEEE Access* 12: 35351–35365. https://doi.org/10.1109/ACCESS.2024.3365192.

Kantipudi, M. V. V. P., N. S. P. Kumar, R. Aluvalu, S. Selvarajan, and K. Kotecha. 2024. "An Improved GBSO-TAENN-Based EEG Signal Classification Model for Epileptic Seizure Detection." *Scientific Reports* 14, no. 1: 843. https://doi.org/10.1038/s41598-024-51337-8.

Karoly, P., M. Cook, L. Kuhlmann, et al. Melbourne NeuroVista Seizure Prediction Trial. https://figshare.unimelb.edu.au/articles/dataset/Seizure_Data/6939809.Online.

Kessler, R. C., and P. S. Wang. 2008. "The Descriptive Epidemiology of Commonly Occurring Mental Disorders in the United States." *Annual Review of Public Health* 29, no. 1: 115–129. https://doi.org/10.1146/annurev.publhealth.29.020907.090847.

Khare, S. K., and U. R. Acharya. 2023. "Adazd-Net: Automated Adaptive and Explainable Alzheimer's Disease Detection System Using EEG Signals." *Knowledge-Based Systems* 278: 110858. https://doi.org/10.1016/j.knosys.2023.110858.

Khosla, A., P. Khandnor, and T. Chand. 2020. "A Comparative Analysis of Signal Processing and Classification Methods for Different Applications Based on EEG Signals." *Biocybernetics and Biomedical Engineering* 40, no. 2: 649–690. https://doi.org/10.1016/j.bbe.2020.02.002.

Kim, H., S. Song, B. H. Cho, and D. P. Jang. 2024. "Deep Learning-Based Stress Detection for Daily Life Use Using Single-Channel EEG and GSR in a Virtual Reality Interview Paradigm." *PLoS One* 19, no. 7: e0305864. https://doi.org/10.1371/journal.pone.0305864.

Kim, J., J. Lee, E. Park, and J. Han. 2020a. "A Deep Learning Model for Detecting Mental Illness From User Content on Social Media." *Scientific Reports* 10, no. 1: 11846. https://doi.org/10.1038/s41598-020-68764-y.

Kim, J. Y., H. S. Lee, and S. H. Lee. 2020. "Eeg Source Network for the Diagnosis of Schizophrenia and the Identification of Subtypes Based on Symptom Severity—A Machine Learning Approach." *Journal of Clinical Medicine* 9, no. 12: 1–13. https://doi.org/10.3390/jcm9123934.

Kim, Y., X. Jiang, S. Lhatoo, et al. 2020. "A Community Effort for Automatic Detection of Postictal Generalized EEG Suppression in Epilepsy." *BMC Medical Informatics and Decision Making* 20, no. S12: 328. https://doi.org/10.1186/s12911-020-01306-8.

Kode, H., K. Elleithy, and L. Almazaydeh. 2024. "Epileptic Seizure Detection in EEG Signals Using Machine Learning and Deep Learning Techniques." *IEEE Access* 12: 80657–80668. https://doi.org/10.1109/ACCESS.2024.3409581.

Kuhlmann, L., L. Lopez, M. O'Connell, et al. n.d. Melbourne-University AES-MathWorks-NIH Seizure Prediction Challenge Accessed September 2, 2024. https://www.kaggle.com/c/melbourne-university-seizure-prediction.

Kunekar, P., M. K. Gupta, and P. Gaur. 2024. "Detection of Epileptic Seizure in EEG Signals Using Machine Learning and Deep Learning Techniques." *Journal of Engineering and Applied Science* 71, no. 1: 21. https://doi.org/10.1186/s44147-023-00353-y.

2022. "Global, Regional, and National Burden of 12 Mental Disorders in 204 Countries and Territories, 1990–2019: A Systematic Analysis for the Global Burden of Disease Study 2019." *Lancet Psychiatry* 9, no. 2: 137–150. https://doi.org/10.1016/S2215-0366(21)00395-3.

Laursen, T. M., M. Nordentoft, and P. B. Mortensen. 2014. "Excess Early Mortality in Schizophrenia." *Annual Review of Clinical Psychology* 10, no. 1: 425–448. https://doi.org/10.1146/annurev-clinpsy-032813-153657.

Leal, A., J. Curty, F. Lopes, et al. 2023. "Unsupervised EEG Preictal Interval Identification in Patients With Drug-Resistant Epilepsy."

Scientific Reports 13, no. 1: 784. https://doi.org/10.1038/s41598-022-23902-6.

Li, K., J. Wang, S. Li, et al. 2021. "Feature Extraction and Identification of Alzheimer's Disease Based on Latent Factor of Multi-Channel EEG." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 29: 1557–1567. https://doi.org/10.1109/TNSRE.2021.3101240.

Li, L., P. Wang, S. Li, et al. 2023. "Construction of a Resting EEG-Based Depression Recognition Model for College Students and Possible Mechanisms of Action of Different Types of Exercise." *BMC Psychiatry* 23, no. 1: 849. https://doi.org/10.1186/s12888-023-05352-0.

Li, M., N. Yuan, J. I. Nurnberger, et al. 2023. "A Pilot Pharmacogenetic Study of Calcium Channel Blocker Treatment of Bipolar Mania." *Psychiatry Research* 326: 115281. https://doi.org/10.1016/j.psychres.2023.115281.

Li, Y., Y. Fang, X. Ren, and L. Gao. 2024. "EEG-Based Depression Recognition Using Feature Selection Method With Fuzzy Label." *Journal of King Saud University - Computer and Information Sciences* 36, no. 3: 102004. https://doi.org/10.1016/j.jksuci.2024.102004.

Lih, O. S., V. Jahmunah, E. E. Palmer, et al. 2023. "EpilepsyNet: Novel Automated Detection of Epilepsy Using Transformer Model With EEG Signals From 121 Patient Population." *Computers in Biology and Medicine* 164: 107312. https://doi.org/10.1016/j.compbiomed.2023.107312.

Lin, H., J. Jia, J. Qiu, et al. 2017. "Detecting Stress Based on Social Interactions in Social Networks." *IEEE Transactions on Knowledge and Data Engineering* 29, no. 9: 1820–1833. https://doi.org/10.1109/TKDE.2017.2686382.

Liu, W., K. Jia, and Z. Wang. 2024. "Graph-Based EEG Approach for Depression Prediction: Integrating Time-Frequency Complexity and Spatial Topology." *Frontiers in Neuroscience* 18: 1367212. https://doi.org/10.3389/fnins.2024.1367212.

Liu, X., C. Li, X. Lou, et al. 2024. "Epileptic Seizure Prediction Based on EEG Using Pseudo-Three-Dimensional CNN." *Frontiers in Neuroinformatics* 18: 1–14. https://doi.org/10.3389/fninf.2024.1354436.

Lord, C., T. S. Brugha, T. Charman, et al. 2020. "Autism Spectrum Disorder." *Nature Reviews. Disease Primers* 6, no. 1: 5. https://doi.org/10.1038/s41572-019-0138-4.

Lundberg, S., and S.-I. Lee. 2017. "A Unified Approach to Interpreting Model Predictions," Accessed September 3, 2024. https://arxiv.org/abs/1705.07874.

Luo, G., H. Rao, P. An, et al. 2023. "Exploring Adaptive Graph Topologies and Temporal Graph Networks for EEG-Based Depression Detection." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 31: 3947–3957. https://doi.org/10.1109/TNSRE.2023.3320693.

Maas, A. I. R., D. K. Menon, G. T. Manley, et al. 2022. "Traumatic Brain Injury: Progress and Challenges in Prevention, Clinical Care, and Research." *Lancet Neurology* 21, no. 11: 1004–1060. https://doi.org/10.1016/S1474-4422(22)00309-X.

Malhi, G. S., P. B. Mitchell, and S. Salim. 2003. "Bipolar Depression." *CNS Drugs* 17, no. 1: 9–25. https://doi.org/10.2165/00023210-200317010-00002.

Malviya, L., and S. Mal. 2022. "A Novel Technique for Stress Detection From EEG Signal Using Hybrid Deep Learning Model." *Neural Computing and Applications* 34, no. 22: 19819–19830. https://doi.org/10.1007/s00521-022-07540-7.

Masters, C. L., R. Bateman, K. Blennow, C. C. Rowe, R. A. Sperling, and J. L. Cummings. 2015. "Alzheimer's Disease." *Nature Reviews. Disease Primers* 1, no. 1: 15056. https://doi.org/10.1038/nrdp.2015.56.

McBride, J. C., X. Zhao, N. B. Munro, et al. 2015. "Sugihara Causality Analysis of Scalp EEG for Detection of Early Alzheimer's Disease." *NeuroImage: Clinical* 7: 258–265. https://doi.org/10.1016/j.nicl.2014.12.005.

Mental Health America. n.d. What Is Mental Illness? Accessed September 6, 2024. https://www.mhanational.org/recognizing-warning-signs.

Mental Health and COVID-19. 2022. "Early Evidence of the Pandemic's Impact: Scientific Brief." Accessed January 13, 2024. https://iris.who.int/bitstream/handle/10665/352189/WHO-2019-nCoV-Sci-Brief-Mental-health-2022.1-eng.pdf?sequence=1.

Miltiadous, A., E. Gionanidis, K. D. Tzimourta, N. Giannakeas, and A. T. Tzallas. 2023. "DICE-Net: A Novel Convolution-Transformer Architecture for Alzheimer Detection in EEG Signals." *IEEE Access* 11: 71840–71858. https://doi.org/10.1109/ACCESS.2023.3294618.

Mishra, S., H. K. Tripathy, H. K. Thakkar, D. Garg, K. Kotecha, and S. Pandya. 2021. "An Explainable Intelligence Driven Query Prioritization Using Balanced Decision Tree Approach for Multi-Level Psychological Disorders Assessment." *Frontiers in Public Health* 9: 795007. https://doi.org/10.3389/fpubh.2021.795007.

Mitchell, T. M., and T. M. Mitchell. 1997. *Machine Learning*. Vol. 1, 9. McGraw-hill.

Naren, J., and A. R. Babu. 2024. "EEG Stress Classification Based on Doppler Spectral Features for Ensemble 1D-CNN With LCL Activation Function." *Journal of King Saud University - Computer and Information Sciences* 36, no. 4: 102013. https://doi.org/10.1016/j.jksuci.2024.102013.

Naser, M. Z., and A. H. Alavi. 2023. "Error Metrics and Performance Fitness Indicators for Artificial Intelligence and Machine Learning in Engineering and Sciences." *Architecture, Structures and Construction* 3, no. 4: 499–517. https://doi.org/10.1007/s44150-021-00015-8.

Nasreddine, W. n.d. Epileptic EEG Dataset Accessed September 3, 2024. https://data.mendeley.com/datasets/5pc2j46cbc/1.

Nejedly, P., et al. 2020. "Multicenter Intracranial EEG Dataset for Classification of Graphoelements and Artifactual Signals." *Scientific Data* 7, no. 1: 179. https://doi.org/10.1038/s41597-020-0532-5.

Nicolas-Alonso, L. F., and J. Gomez-Gil. 2012. "Brain Computer Interfaces, a Review." *Sensors* 12, no. 2: 1211–1279. https://doi.org/10.3390/s120201211.

Niedermeyer, E., and F. H. Lopes da Silva. 2005. *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*. Lippincott Williams & Wilkins.

Obayya, M., M. K. Saeed, M. Maashi, S. S. Alotaibi, A. S. Salama, and M. A. Hamza. 2023. "A Novel Automated Parkinson's Disease Identification Approach Using Deep Learning and EEG." *PeerJ Computer Science* 9: e1663. https://doi.org/10.7717/peerj-cs.1663.

Osheroff, J. 2012. *Improving Outcomes With Clinical Decision Support*. HIMSS Publishing. https://doi.org/10.4324/9781498757461.

Page, M. J., J. E. McKenzie, P. M. Bossuyt, et al. 2021. "The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews." *BMJ* 372: 1–9. https://doi.org/10.1136/bmj.n71.

Peiffer-Smadja, N., et al. 2020. "Machine Learning for Clinical Decision Support in Infectious Diseases: A Narrative Review of Current Applications." *Clinical Microbiology and Infection* 26, no. 5: 584–595. https://doi.org/10.1016/j.cmi.2019.09.009.

Peng, H., C. Xia, Z. Wang, et al. 2019. "Multivariate Pattern Analysis of EEG-Based Functional Connectivity: A Study on the Identification of Depression." *IEEE Access* 7: 92630–92641. https://doi.org/10.1109/ACCESS.2019.2927121.

Perera, M. P. N., S. Mallawaarachchi, N. W. Bailey, O. W. Murphy, and P. B. Fitzgerald. 2023. "Obsessive-Compulsive Disorder (OCD) is Associated With Increased Electroencephalographic (EEG) Delta and Theta Oscillatory Power but Reduced Delta Connectivity." *Journal of*

Psychiatric Research 163: 310–317. https://doi.org/10.1016/j.jpsychires.2023.05.026.

Perez-Valero, E., C. Morillas, M. A. Lopez-Gordo, and J. Minguillon. 2023. "Supporting the Detection of Early Alzheimer's Disease With a Four-Channel EEG Analysis." *International Journal of Neural Systems* 33, no. 4: 2350021. https://doi.org/10.1142/S0129065723500211.

Raeisi, K., M. Khazaei, P. Croce, G. Tamburro, S. Comani, and F. Zappasodi. 2022. "A Graph Convolutional Neural Network for the Automated Detection of Seizures in the Neonatal EEG." *Computer Methods and Programs in Biomedicine* 222: 106950. https://doi.org/10.1016/j.cmpb.2022.106950.

Rafiei, A., R. Zahedifar, C. Sitaula, and F. Marzbanrad. 2022. "Automated Detection of Major Depressive Disorder With EEG Signals: A Time Series Classification Using Deep Learning." *IEEE Access* 10: 73804–73817. https://doi.org/10.1109/ACCESS.2022.3190502.

Rahul, J., D. Sharma, L. D. Sharma, U. Nanda, and A. K. Sarkar. 2024. "A Systematic Review of EEG Based Automated Schizophrenia Classification Through Machine Learning and Deep Learning." *Frontiers in Human Neuroscience* 18: 1347082. https://doi.org/10.3389/fnhum.2024.1347082.

Rakofsky, J., and M. Rapaport. 2018. "Mood Disorders." *CONTINUUM: Lifelong Learning in Neurology* 24, no. 3: 804–827. https://doi.org/10.1212/CON.0000000000000604.

Rantala, M. J., S. Luoto, J. I. Borráz-León, and I. Krams. 2022. "Schizophrenia: The New Etiological Synthesis." *Neuroscience & Biobehavioral Reviews* 142: 104894. https://doi.org/10.1016/j.neubiorev.2022.104894.

Rashid, M., N. Sulaiman, A. P. P. Abdul Majeed, et al. 2020. "Current Status, Challenges, and Possible Solutions of EEG-Based Brain-Computer Interface: A Comprehensive Review." *Frontiers in Neurorobotics* 14: 1–35. https://doi.org/10.3389/fnbot.2020.00025.

Reddy, G. R. S., and R. Rao. 2017. "Automated Identification System for Seizure EEG Signals Using Tunable-Q Wavelet Transform." *Engineering Science and Technology, an International Journal* 20, no. 5: 1486–1493. https://doi.org/10.1016/j.jestch.2017.11.003.

Ribeiro, M. T., S. Singh, and C. Guestrin. 2016. 'Why Should I Trust You?': Explaining the Predictions of any Classifier Accessed September08, 2024. https://arxiv.org/abs/1602.04938.

Rivera, M. J., J. Sanchis, O. Corcho, M. A. Teruel, and J. Trujillo. 2024. "Evaluating CNN Methods for Epileptic Seizure Type Classification Using EEG Data." *IEEE Access* 12: 75483–75495. https://doi.org/10.1109/ACCESS.2024.3406332.

Rivera, M. J., M. A. Teruel, A. Maté, and J. Trujillo. 2022. "Diagnosis and Prognosis of Mental Disorders by Means of EEG and Deep Learning: A Systematic Mapping Study." *Artificial Intelligence Review* 55, no. 2: 1209–1251. https://doi.org/10.1007/s10462-021-09986-y.

Ross, C. A., E. H. Aylward, E. J. Wild, et al. 2014. "Huntington Disease: Natural History, Biomarkers and Prospects for Therapeutics." *Nature Reviews. Neurology* 10, no. 4: 204–216. https://doi.org/10.1038/nrneurol.2014.24.

Ruiz Marín, M., I. Villegas Martínez, G. Rodríguez Bermúdez, and M. Porfiri. 2021. "Integrating Old and New Complexity Measures Toward Automated Seizure Detection From Long-Term Video EEG Recordings." *iScience* 24, no. 1: 101997. https://doi.org/10.1016/j.isci.2020.101997.

Saffari, F., K. Norouzi, L. E. Bruni, S. Zarei, and T. Z. Ramsøy. 2023. "Impact of Varying Levels of Mental Stress on Phase Information of EEG Signals: A Study on the Frontal, Central, and Parietal Regions." *Biomedical Signal Processing and Control* 86: 105236. https://doi.org/10.1016/j.bspc.2023.105236.

Safi, M. S., and S. M. M. Safi. 2021. "Early Detection of Alzheimer's Disease From EEG Signals Using Hjorth Parameters." *Biomedical Signal Processing and Control* 65: 102338. https://doi.org/10.1016/j.bspc.2020.102338.

Sarkar, A., A. Singh, and R. Chakraborty. 2022. "A Deep Learning-Based Comparative Study to Track Mental Depression From EEG Data." *Neuroscience Informatics* 2, no. 4: 100039. https://doi.org/10.1016/j.neuri.2022.100039.

Saxena, S., and E. Krug. 2013. *Mental Health Action Plan 2013–2020*. World Health Organization Publications.

Selvaraju, R. R., M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra. 2020. "Grad-CAM: Visual Explanations From Deep Networks via Gradient-Based Localization." *International Journal of Computer Vision* 128, no. 2: 336–359. https://doi.org/10.1007/s11263-019-01228-7.

Seoni, S., V. Jahmunah, M. Salvi, P. D. Barua, F. Molinari, and U. R. Acharya. 2023. "Application of Uncertainty Quantification to Artificial Intelligence in Healthcare: A Review of Last Decade (2013–2023)." *Computers in Biology and Medicine* 165: 107441. https://doi.org/10.1016/j.compbiomed.2023.107441.

Serretti, A. 2023. "Anhedonia and Depressive Disorders." *Clinical Psychopharmacology and Neuroscience* 21, no. 3: 401–409. https://doi.org/10.9758/cpn.23.1086.

Shah, S. J. H., A. Albishri, S. S. Kang, Y. Lee, S. R. Sponheim, and M. Shim. 2023. "ETSNet: A Deep Neural Network for EEG-Based Temporal–Spatial Pattern Recognition in Psychiatric Disorder and Emotional Distress Classification." *Computers in Biology and Medicine* 158: 106857. https://doi.org/10.1016/j.compbiomed.2023.106857.

Shanthalakshmi Revathy, J., N. Uma Maheswari, S. Sasikala, and R. Venkatesh. 2024. "Automatic Diagnosis of Mental Illness Using Optimized Dynamically Stabilized Recurrent Neural Network." *Biomedical Signal Processing and Control* 95: 106321. https://doi.org/10.1016/j.bspc.2024.106321.

Sharma, G., A. M. Joshi, R. Gupta, and L. R. Cenkeramaddi. 2023. "DepCap: A Smart Healthcare Framework for EEG Based Depression Detection Using Time-Frequency Response and Deep Neural Network." *IEEE Access* 11: 52327–52338. https://doi.org/10.1109/ACCESS.2023.3275024.

Shen, J., Y. Zhang, H. Liang, et al. 2023. "Exploring the Intrinsic Features of EEG Signals via Empirical Mode Decomposition for Depression Recognition." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 31: 356–365. https://doi.org/10.1109/TNSRE.2022.3221962.

Shen, M., F. Yang, P. Wen, B. Song, and Y. Li. 2024. "A Real-Time Epilepsy Seizure Detection Approach Based on EEG Using Short-Time Fourier Transform and Google-Net Convolutional Neural Network." *Heliyon* 10, no. 11: e31827. https://doi.org/10.1016/j.heliyon.2024.e31827.

Sheykhivand, S., T. Y. Rezaii, Z. Mousavi, A. Delpak, and A. Farzamnia. 2020. "Automatic Identification of Epileptic Seizures From EEG Signals Using Sparse Representation-Based Classification." *IEEE Access* 8: 138834–138845. https://doi.org/10.1109/ACCESS.2020.3011877.

Shoji, T., N. Yoshida, and T. Tanaka. 2021. "Automated Detection of Abnormalities From an EEG Recording of Epilepsy Patients With a Compact Convolutional Neural Network." *Biomedical Signal Processing and Control* 70: 103013. https://doi.org/10.1016/j.bspc.2021.103013.

Sigcha, L., L. Borzì, F. Amato, et al. 2023. "Deep Learning and Wearable Sensors for the Diagnosis and Monitoring of Parkinson's Disease: A Systematic Review." *Expert Systems with Applications* 229: 120541. https://doi.org/10.1016/j.eswa.2023.120541.

Sim, I., P. Gorman, R. A. Greenes, et al. 2001. "Clinical Decision Support Systems for the Practice of Evidence-Based Medicine." *Journal of the American Medical Informatics Association* 8, no. 6: 527–534. https://doi.org/10.1136/jamia.2001.0080527.

Simpraga, S., R. Alvarez-Jimenez, H. D. Mansvelder, et al. 2017. "EEG Machine Learning for Accurate Detection of Cholinergic Intervention

and Alzheimer's Disease." *Scientific Reports* 7, no. 1: 5775. https://doi.org/10.1038/s41598-017-06165-4.

Singh, A., T. M. Dawson, and S. Kulkarni. 2021. "Neurodegenerative Disorders and Gut-Brain Interactions." *Journal of Clinical Investigation* 131, no. 13: e143775. https://doi.org/10.1172/JCI143775.

Stevenson, N., K. Tapani, L. Lauronen, and S. Vanhatalo. n.d. Helsinki University Hospital Neonatal EEG Accessed September 2, 2024. https://zenodo.org/records/4940267.

Stieger, J. R., S. A. Engel, and B. He. 2021. "Continuous Sensorimotor Rhythm Based Brain Computer Interface Learning in a Large Population." *Scientific Data* 8, no. 1: 98. https://doi.org/10.1038/s41597-021-00883-1.

Su, C., Z. Xu, J. Pathak, and F. Wang. 2020. "Deep Learning in Mental Health Outcome Research: A Scoping Review." *Translational Psychiatry* 10, no. 1: 116. https://doi.org/10.1038/s41398-020-0780-3.

Sun, J., R. Cao, M. Zhou, et al. 2021. "A Hybrid Deep Neural Network for Classification of Schizophrenia Using EEG Data." *Scientific Reports* 11, no. 1: 4706. https://doi.org/10.1038/s41598-021-83350-6.

Sunaryono, D., R. Sarno, and J. Siswantoro. 2022. "Gradient Boosting Machines Fusion for Automatic Epilepsy Detection From EEG Signals Based on Wavelet Features." *Journal of King Saud University - Computer and Information Sciences* 34, no. 10: 9591–9607. https://doi.org/10.1016/j.jksuci.2021.11.015.

Swami, P., B. K. Panigrahi, S. Nara, M. Bhatia, and T. K. Gandhi. Neurology and Sleep Centre Hauz Khas Dataset.

Tasci, G., M. V. Gun, T. Keles, et al. 2023. "QLBP: Dynamic Patterns-Based Feature Extraction Functions for Automatic Detection of Mental Health and Cognitive Conditions Using EEG Signals." *Chaos, Solitons and Fractals* 172: 113472. https://doi.org/10.1016/j.chaos.2023.113472.

Tawhid, M. N. A., S. Siuly, H. Wang, F. Whittaker, K. Wang, and Y. Zhang. 2021. "A Spectrogram Image Based Intelligent Technique for Automatic Detection of Autism Spectrum Disorder From EEG." *PLoS One* 16, no. 6: e0253094. https://doi.org/10.1371/journal.pone.0253094.

Telesford, Q. K., E. Gonzalez-Moreira, T. Xu, et al. 2022. "Naturalistic Viewing: An Open-Access Dataset Using Simultaneous EEG-fMRI." *bioRxiv*.

Terpou, B. A., S. B. Shaw, J. Théberge, et al. 2022. "Spectral Decomposition of EEG Microstates in Post-Traumatic Stress Disorder." *NeuroImage: Clinical* 35: 103135. https://doi.org/10.1016/j.nicl.2022.103135.

Thomson, N. D., M. Aboutanos, K. A. Kiehl, C. Neumann, C. Galusha, and K. A. Fanti. 2019. "Physiological Reactivity in Response to a Fear-Induced Virtual Reality Experience: Associations With Psychopathic Traits." *Psychophysiology* 56, no. 1: e13276. https://doi.org/10.1111/psyp.13276.

Tolosa, E., A. Garrido, S. W. Scholz, and W. Poewe. 2021. "Challenges in the Diagnosis of Parkinson's Disease." *Lancet Neurology* 20, no. 5: 385–397. https://doi.org/10.1016/S1474-4422(21)00030-2.

Tuncer, T., S. Dogan, G. R. Naik, and P. Pławiak. 2021. "Epilepsy Attacks Recognition Based on 1D Octal Pattern, Wavelet Transform and EEG Signals." *Multimedia Tools and Applications* 80, no. 16: 25197–25218. https://doi.org/10.1007/s11042-021-10882-4.

Uddin, M. Z., K. K. Dysthe, A. Følstad, and P. B. Brandtzaeg. 2022. "Deep Learning for Prediction of Depressive Symptoms in a Large Textual Dataset." *Neural Computing and Applications* 34, no. 1: 721–744. https://doi.org/10.1007/s00521-021-06426-4.

Uyulan, C., T. T. Ergüzel, H. Unubol, et al. 2021. "Major Depressive Disorder Classification Based on Different Convolutional Neural Network Models: Deep Learning Approach." *Clinical EEG and Neuroscience* 52, no. 1: 38–51. https://doi.org/10.1177/1550059420916634.

Walker, E. R., R. E. McGee, and B. G. Druss. 2015. "Mortality in Mental Disorders and Global Disease Burden Implications." *JAMA Psychiatry* 72, no. 4: 334. https://doi.org/10.1001/jamapsychiatry.2014.2502.

Wang, F., X. Yang, X. Zhang, and F. Hu. 2024c. "Monitoring the After-Effects of Ischemic Stroke Through EEG Microstates." *PLoS One* 19, no. 3: e0300806. https://doi.org/10.1371/journal.pone.0300806.

Wang, J., S. Liang, J. Zhang, et al. 2023. "EEG Signal Epilepsy Detection With a Weighted Neighbor Graph Representation and Two-Stream Graph-Based Framework." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 31: 3176–3187. https://doi.org/10.1109/TNSRE.2023.3299839.

Wang, J., M. Sun, and W. Huang. 2024. "Unsupervised EEG-Based Seizure Anomaly Detection With Denoising Diffusion Probabilistic Models." *International Journal of Neural Systems* 34, no. 9: 2450047. https://doi.org/10.1142/S0129065724500473.

Wang, X., Y. Wang, D. Liu, Y. Wang, and Z. Wang. 2023. "Automated Recognition of Epilepsy From EEG Signals Using a Combining Space–Time Algorithm of CNN-LSTM." *Scientific Reports* 13, no. 1: 14876. https://doi.org/10.1038/s41598-023-41537-z.

Wang, Y., S. Zhao, H. Jiang, et al. 2024. "Diffmdd: A Diffusion-Based Deep Learning Framework for MDD Diagnosis Using EEG." *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 32: 728–738. https://doi.org/10.1109/TNSRE.2024.3360465.

Wong, S. C. P., and M. E. Olver. 2015. "Risk Reduction Treatment of Psychopathy and Applications to Mentally Disordered Offenders." *CNS Spectrums* 20, no. 3: 303–310. https://doi.org/10.1017/S1092852915000322.

Woody, C. A., A. J. Ferrari, D. J. Siskind, H. A. Whiteford, and M. G. Harris. 2017. "A Systematic Review and Meta-Regression of the Prevalence and Incidence of Perinatal Depression." *Journal of Affective Disorders* 219: 86–92. https://doi.org/10.1016/j.jad.2017.05.003.

World Health Organization. n.d. Anxiety Disorders Accessed September 13, 2024. https://www.who.int/news-room/fact-sheets/detail/anxiety-disorders.

World Health Organization (WHO). 2009. "Mental Health Systems in Selected Low- and Middle-Income Countries."

World Health Organization (WHO). Bipolar Disoder Accessed September 13, 2024. https://www.who.int/news-room/fact-sheets/detail/bipolar-disorder.

World Health Organization (WHO). n.d.-a. Depressive Disorder (Depression) Accessed September 13, 2024. https://www.who.int/news-room/fact-sheets/detail/depression.

World Health Organization (WHO). n.d.-c. Schizophrenia Accessed September 13, 2024. https://www.who.int/news-room/fact-sheets/detail/schizophrenia.

Xiaoli, W., Z. Wenhui, F. Zhibo, T. H. C. Roy, and R. H. M. Chan. 2020. Ear-Eeg Recording for Brain Computer Interface of Motor Task Accessed September 2, 2024. https://ieee-dataport.org/open-access/ear-eeg-recording-brain-computer-interface-motor-task.

Xiong, H., X. Li, X. Zhang, et al. 2024. "Towards Explainable Artificial Intelligence (XAI): A Data Mining Perspective." Accessed September 3, 2024. https://arxiv.org/abs/2401.04374v2.

Xiong, Z., Y. Liu, and P. Jiang. 2024. "An EEG-Based Seizure Recognition Method Using Dynamic Routing." *IEEE Access* 12: 74054–74068. https://doi.org/10.1109/ACCESS.2024.3402075.

Xu, Y., Z. Yu, Y. Li, Y. Liu, Y. Li, and Y. Wang. 2024. "Autism Spectrum Disorder Diagnosis With EEG Signals Using Time Series Maps of Brain Functional Connectivity and a Combined CNN–LSTM Model." *Computer Methods and Programs in Biomedicine* 250: 108196. https://doi.org/10.1016/j.cmpb.2024.108196.

Yasin, S., A. Othmani, I. Raza, and S. A. Hussain. 2023. "Machine Learning Based Approaches for Clinical and Non-Clinical Depression Recognition and Depression Relapse Prediction Using Audiovisual and EEG Modalities: A Comprehensive Review." *Computers in Biology and Medicine* 159: 106741. https://doi.org/10.1016/j.compbiomed.2023.106741.

Yazid, M., F. Fahmi, E. Sutanto, et al. 2021. "Simple Detection of Epilepsy From EEG Signal Using Local Binary Pattern Transition Histogram." *IEEE Access* 9: 150252–150267. https://doi.org/10.1109/ACCESS.2021.3126065.

Yehuda, R., C. W. Hoge, A. C. McFarlane, et al. 2015. "Post-Traumatic Stress Disorder." *Nature Reviews. Disease Primers* 1, no. 1: 15057. https://doi.org/10.1038/nrdp.2015.57.

Yuan, J., X. Ran, K. Liu, et al. 2022. "Machine Learning Applications on Neuroimaging for Diagnosis and Prognosis of Epilepsy: A Review." *Journal of Neuroscience Methods* 368: 109441. https://doi.org/10.1016/j.jneumeth.2021.109441.

Zazzaro, G., and L. Pavone. 2022. "Machine Learning Characterization of Ictal and Interictal States in EEG Aimed at Automated Seizure Detection." *Biomedicine* 10, no. 7: 1491. https://doi.org/10.3390/biomedicines10071491.

Zhang, X., L. Yao, X. Wang, J. Monaghan, D. McAlpine, and Y. Zhang. 2021. "A Survey on Deep Learning-Based Non-Invasive Brain Signals: Recent Advances and New Frontiers." *Journal of Neural Engineering* 18, no. 3: 031002. https://doi.org/10.1088/1741-2552/abc902.

Zhou, Z., Y. Majeed, G. Diverres Naranjo, and E. M. T. Gambacorta. 2021. "Assessment for Crop Water Stress With Infrared Thermal Imagery in Precision Agriculture: A Review and Future Prospects for Deep Learning Applications." *Computers and Electronics in Agriculture* 182: 106019. https://doi.org/10.1016/j.compag.2021.106019.

Zhu, J., Y. Wang, R. la, et al. 2019. "Multimodal Mild Depression Recognition Based on EEG-EM Synchronization Acquisition Network." *IEEE Access* 7: 28196–28210. https://doi.org/10.1109/ACCESS.2019.2901950.

Zhu, X., H. Xu, J. Zhao, and J. Tian. 2017. "Automated Epileptic Seizure Detection in Scalp EEG Based on Spatial-Temporal Complexity." *Complexity* 2017: 1–8. https://doi.org/10.1155/2017/5674392.

Appendix A

Information About Extracted Papers

TABLE A1 | Depression related studies.

Author	Disease	Subject	Electrodes	Classifier	Accuracy (%)	Sensitivity	Specificity	AUC	F1
(Cai et al. 2018)	Depression	213 (92 Depressed/121 HC)	3-Channel	SVM kNN CT ANN	69.51 76.98 66.93 73.02	N/A	N/A	N/A	N/A
(Peng et al. 2019)	Depression	55 (27 Depressed/28 HC)	128-Channel	SVM KNN DT NB	All: 92.73,78.18, 85.46, 85.46 Delta: 90.91, 80, 74.55, 83.64 Theta: 90.91, 85.46, 72.73, 87.27 Alpha: 80, 76.36, 72.73, 78.18 Beta: 87.27, 78.18, 81.82, 83.64	N/A	N/A	0.98 0.95 0.94 0.94	N/A
(Zhu et al. 2019)	Depression	51 (36 Males, 15 Females)	16-Channel	Linear SVM RBF SVM GBD Tree RF Self-Normalizing Network BNMLP	83.42 80.85 78.46 76.58 78.29 76.92	N/A	N/A	N/A	N/A
(Rafiei et al. 2022)	Major Depressive Disorder	64 (34 MDD (17 Females, 17 Males))/ 30 HC (9 Females, 21 Males)	19-Channel	DNN	10-Channel: 90.1 19-Channel: 91	10-Channel: 93.2 19-Channel: 94.9	10-Channel: 88.2 19-Channel: 88.2	N/A	N/A
(Luo et al. 2023)	Depression	Dataset 1: 122 (46 Depression/76 HC) Dataset 2: 40 (18 Depression/22 HC)	Dataset 1: 66-Channel Dataset 2: 18-Channel	GNN	Dataset 1: 77.78 Dataset 2: 95.61	N/A	N/A	Dataset 1: 0.83 Dataset 2: 0.99	Dataset 1: 82.75 Dataset 2: 94.61

(Continues)

TABLE A1 | (Continued)

Author	Disease	Subject	Electrodes	Classifier	Accuracy (%)	Sensitivity	Specificity	AUC	F1
(Garg et al. 2023)	Depression	120 (62 Major Depressive Disorder/58 HC)	20-Channel	Spectral Clustering with K-means Algorithm	Left Hemisphere: 98 Right Hemisphere: 97	Left Hemisphere: 95 Right Hemisphere: 97	Left Hemisphere: 100 Right Hemisphere: 97	N/A	N/A
(Li, Wang et al. 2023)	Depression	140	16-Channel	Regression	N/A	N/A	N/A	Training Group: 0.791 Validation Group: 0.786	N/A
(Shen et al. 2023)	Depression	Dataset 1: 53(24 Depressed/29 HC) Dataset 2: 35 (15 Depressed/20 HC) Dataset 3: 170 (81 Depressed/89 HC) Dataset 4: 214 (105 Depressed/109 HC)	Dataset 1: 128-Channel Dataset 2: 64-Channel Dataset 3: 3-Channel Dataset 4: 3-Channel	SVM kNN DT	Dataset 1: 87.50 81.25 80 Dataset 2: 88.50 84.50 80.75 Dataset 3: 84.85 78.24 77.06 Dataset 4: 78.77 69.36 65.86	Dataset 1: 87.50 75 72.50 Dataset 2: 87.50 97.92 82.50 Dataset 3: 78.75 87.78 81.11 Dataset 4: 76 81.36 66.36	Dataset 1: 87.50 87.50 87.50 Dataset 2: 89.17 64.38 78.13 Dataset 3: 90.28 67.50 72.50 Dataset 4: 81.55 57.36 65.36	N/A	N/A
(Sharma et al. 2023)	Depression	94 (64 Depressed/30 HC)	19-Channel	LSTM-CNN	99.9	100	99.8	N/A	N/A
(Chung et al. 2024)	Depression	214 (142 Depressed/42 HC)	1-Channel (FP1)	LSTM-DNN	89.7	N/A	87.5	0.8917	92.1
(Li et al. 2024)	Depression	53 (24 Depressed/29 HC)	125-Channel	FLFCFS	92.59	94.74	91.30	0.9243	92.60
(Liu, Jia et al. 2024)	Depression	Dataset 1: 53 (23 Depressed/29 HC) Dataset 2: 119 (44 Depressed/75 HC)	Dataset 1: 128-Channel Dataset 2: 64-Channel	GCNN	98.30 96.51	N/A	N/A	N/A	N/A

TABLE A2 | Parkinson's disease related studies.

Author	Disease	Subject	Electrodes	Classifier	Accuracy (%)	Sensitivity	Specificity	AUC	F1
(Cao et al. 2021)	Parkinson's disease	17	32-Channel	Linear SVM Kernel SVM kNN RF	68.09 79.44 73.21 73.02	68.42 84.12 88.49 79.69	66.21 73.80 54.36 66.91	N/A	68.30 79.32 72.11 72.94
(Aljalal et al. 2022)	Parkinson's disease	Dataset 1: 31(15 PD/16 HC) Dataset 2: 54 (27 PD/27 HC)	Dataset 1/2: 32-Channel	LR LDA RF SVM kNN	Dataset 1: kNN:99.89 Dataset 2: SVM:99.51 kNN:99.52	Dataset 1: kNN:99.87	Dataset 1: kNN:99.91	Dataset 1: 0.99 1 0.99 1 1 Dataset 2: 0.88 0.99 0.97 0.98 0.99	N/A
(Obayya et al. 2023)	Parkinson's disease	31 (15 PD/16 HC)	32-Channel	LSTM	99.6	99	100	0.99	99

TABLE A3 | Stress related studies.

Author	Disease	Subject	Electrodes	Classifier	Accuracy (%)	Sensitivity	Specificity	AUC	F1
(Chai and Ba 2021)	Stress	N/A	64-Channel	NN	80	N/A	N/A	N/A	N/A
(Terpou et al. 2022)	Post Traumatic Stress Disorder	Dataset 1: 50 (20 PTSD/30 HC) Dataset 2: 73 (41 PTSD/32 HC)	19-Channel	SVM	76 (Alpha Band) 65 (Broadband)	79 (Alpha Band) 72 (Broadband)	74 (Alpha Band) 62 (Broadband)	0.75 (Alpha Band) 0.71 (Broadband)	N/A
(Saffari et al. 2023)	Stress	41 (21 Male/20 Female)	9-Channel	RF	83.78	N/A	N/A	N/A	83.21
(Kim et al. 2024)	Stress	29	1-Channel	DL	Inception-v3: 88.6 ResNet-50: 86.5 ResNet-152: 88.9 DenseNet-161: 78.4 EfficientNet-b0: 86.7 Vision Transformer: 88.2	N/A	N/A	Inception-v3: 0.943 ResNet-50: 0.954 ResNet-152: 0.946 DenseNet-161: 0.907 EfficientNet-b0: 0.948 Vision Transformer: 0.945	Inception-v3: 91.8 ResNet-50: 89.8 ResNet-152: 91.8 DenseNet-161: 84.2 EfficientNet-b0: 89.4 Vision Transformer: 91.8
(Naren and Babu 2024)	Stress	40 (14 Female/26 Male)	32-Channel	1D-CNN	95.25	N/A	99.41	N/A	93.98

TABLE A4 | Schizophrenia related studies.

Author	Disease	Subject	Electrodes	Classifier	Accuracy (%)	Sensitivity	Specificity	AUC	F1
(Kim, Lee, and Lee 2020)	Schizophrenia	238 (119 SZ/119 HC)	64-Channel	LDA	80.66	78.83	82.48	N/A	N/A
(Barros et al. 2022)	Schizophrenia	128 (65 SZ/63 HC)	64-Channel	RF CNN	73 78	N/A	76 79	0.73 0.78	N/A
(Aksoy et al. 2024)	Schizophrenia	84 (39 HC/45 Adolescent Males)	16-Channel	QSVM	100	100	100	N/A	N/A
(Garip et al. 2024)	Schizophrenia	28 (14 SZ/14 HC)	19-Channel	DT RF ET	95 97.14 97.36	N/A	N/A	N/A	N/A

TABLE A5 | Alzheimer's disease related studies.

Author	Disease	Subject	Electrodes	Classifier	Accuracy (%)	Sensitivity	Specificity	AUC	F1
(McBride et al. 2015)	Alzheimer's Disease	48 (15 HC/16 Mild Cognitive Impairment/17 Early-Stage AD)	30-Channel	SVM	Resting eyes open: 95.8 Counting eyes closed: 95.8 Resting eyes closed: 97.9	N/A	N/A	N/A	N/A
(Simpraga et al. 2017)	Alzheimer's Disease	4	5-Channel (Fz, Cz, Pz, Oz, Eye Movements)	LR	95	96	93	0.98	N/A
(Fan et al. 2018)	Alzheimer's Disease	123 (15 HC/15 Clinical Dementia Rating 0.5/69 CDR 1/24 CDR 2)	19-Channel	LR	80	N/A	N/A	N/A	N/A
(Safi and Safi 2021)	Alzheimer's Disease	86 (35 HC/31 mild AD/20 moderate AD)	20-Channel	SVM kNN RLDA	95.79 97.64 97.02	91.93 95.40 94.22	97.85 98.81 98.49	N/A	N/A
(Li et al. 2021)	Alzheimer's Disease	40 (20 AD/20 HC)	16-Channel	Takagi-Sugeno-Kang Classifier SVM LDA NB kNN	98.10 93.61 88.71 94.95 91.60	98.02 90.21 79.95 88.62 93.34	98.06 91.55 89.04 93.60 88.96	N/A	N/A
(Khare and Acharya 2023)	Alzheimer's Disease	23 (12 AD/11 HC)	16-Channel	ML-DL	99.85	99.75	100	N/A	99.88
(Perez-Valero et al. 2023)	Alzheimer's Disease	16 (8 AD/8 HC)	16-Channel	LR SVM MLP	87 87 85	N/A	N/A	N/A	N/A

(Continues)

TABLE A5 | (Continued)

Author	Disease	Subject	Electrodes	Classifier	Accuracy (%)	Sensitivity	Specificity	AUC	F1
(Chu et al. 2023)	Alzheimer's Disease	205 (51 Cognitively Normal/42 Mild Cognitive Impairment/61 AD1/35 AD2/16 AD3)	19-Channel	LogitBoost Bag GentleBoost DT SVM NB kNN	76 76 81 73 70 76 70	71 65 82 71 59 82 59	80 85 80 75 80 70 89	N/A	73 71 80 71 65 76 65
(Miltiadous et al. 2023)	Alzheimer's Disease	88 (36 AD/23 Frontotemporal Dementia/29 HC)	19-Channel	CNN	83.28	79.81	87.94	N/A	84.12
(Dogan et al. 2024)	Alzheimer's Disease	9	59-Channel	DL	Experiment 1: 98.37 Experiment 2: 99.62 Experiment 3: 98.74	N/A	N/A	N/A	N/A
(Jasphin Jeni Sharmila and Shiny Angel 2024)	Alzheimer's Disease + Epilepsy	Dataset 1: 25 Dataset 2: 150	Dataset 1: 1-Channel Dataset 2: - (MRI Dataset)	DBN	Dataset 1: 94 Dataset 2: 95.05	N/A	N/A	N/A	Dataset 1- Training: 94.91 Test:93.44 Dataset 2- Training:95.74 Test:94.76

TABLE A6 | Epilepsy-related studies.

Author	Disease	Subject	Electrodes	Classifier	Accuracy (%)	Sensitivity	Specificity	AUC	F1
(Zhu et al. 2017)	Epilepsy	22 (17 Females/5 Males)	23-Bipolar Channel	DA	88.9	N/A	N/A	N/A	N/A
(Abbasi et al. 2019)	Epilepsy	5	128-Channel	LSTM	Binary: 97.25 Multi: 94.81	Binary: 97.11 Multi: 92.63	Binary: 99.07 Multi: 99.43	N/A	N/A
(Kim, Jiang et al. 2020)	Epilepsy	128 (57 Male/71 Female)	13-Channel	CNN	N/A	N/A	N/A	0.77	N/A
(Sheykhivand et al. 2020)	Epilepsy	25 5 Subsets	1-Channel	Sparse Representation-Based Classification	100	100	100	N/A	N/A
(Chen et al. 2020)	Epilepsy	Dataset 1: 5 Dataset 2: 22	Dataset 1: 64-Channel Dataset 2: 23-Channel	SVM	93 94	97.8 100	100 97.9	N/A	N/A
(Yazid et al. 2021)	Epilepsy	25 5 Subsets	1-Channel	SVM kNN	99.82 99.79	99.79 N/A	99.91 N/A	N/A	N/A
(Tuncer et al. 2021)	Epilepsy	25 5 Subsets	1-Channel	kNN	96	N/A	N/A	N/A	N/A
(Shoji et al. 2021)	Epilepsy	29 (19 Childhood Absence Epilepsy/Juvenile Absence Epilepsy)	16-Channel	CNN	N/A	82.4	99.6	0.99	83.7
(Sunaryono et al. 2022)	Epilepsy	25 5 Subsets	1-Channel	GBM	100	N/A	N/A	N/A	N/A
(Wang, Wang et al. 2023)	Epilepsy	25 5 Subsets	128-Channel	CNN-LSTM	98	98.3	97.4	0.968	N/A
(Wang, Liang et al. 2023)	Epilepsy	Dataset 1: 25 5 Subsets Dataset 2: N/A Dataset 3: 23	Dataset 1: 1-Channel Dataset 2: 1-Channel Dataset 3: 23-Channel	GNN	Dataset 1: 99.18 Dataset 2: 95.8 Dataset 3: 93.6	Dataset 1: 99.22 Dataset 2: 94.40 Dataset 3: 89.70	Dataset 1: 99.5 Dataset 2: 97.10 Dataset 3: 96.60	N/A	N/A
(Lih et al. 2023)	Epilepsy	121 (71 EP/50 HC)	35-Channel	Deep Transformer	85	82	87	N/A	N/A
(Islam et al. 2023)	Epilepsy	10 (5 EP/5 HC)	32-Channel	CNN	100	N/A	N/A	N/A	N/A
(Leal et al. 2023)	Epilepsy	41	19-Channel	DNN	N/A	93	94	N/A	N/A
(Chen et al. 2023)	Epilepsy	10 (5 EP/5 HC)	1-Channel	CNN	99.9	100	99.8	N/A	N/A

(Continues)

TABLE A6 | (Continued)

Author	Disease	Subject	Electrodes	Classifier	Accuracy (%)	Sensitivity	Specificity	AUC	F1
(Reddy and Rao 2017)	Epilepsy	5	128-Channel	RF MLP LR	98.3 97.3 96.7	98 96 95	98.5 98 97.5	N/A	N/A
(Ruiz Marín et al. 2021)	Epilepsy	10	19-Channel	RUSBoost	86.64	87.04	87.15	0.93	93
(Zazzaro and Pavone 2022)	Epilepsy	21	128-Channel	kNN	100	N/A	N/A	N/A	98.25
(Gómez et al. 2020)	Epilepsy	Dataset 1: 22 Dataset 2: N/A	Dataset 1: 23-Bipolar Channel Dataset 2: N/A	CNN	Dataset 1: 99.3 Dataset 2: 98	N/A	Dataset 1: 99.6 Dataset 2: 98.3	N/A	N/A
(Kamakshi and Rengaraj 2024)	Epilepsy	Dataset 1: 25 5 Subsets Dataset 2: 22 Dataset 3: 14	1-Channel	LSTM	Dataset 1: 98.5 Dataset 2: 98.5 Dataset 3: 98	N/A	N/A	N/A	N/A
(Kode et al. 2024)	Epilepsy	25 5 Subsets	1-Channel	ML-DL	XGBoost: 98 Tabnet: 96 RF: 98 1D-CNN: 99	N/A	N/A	N/A	XGBoost: 97 Tabnet: 96 RF: 98 1D-CNN: 99
(Xiong, Liu et al. 2024)	Epilepsy	Dataset 1: 25 (5 Subsets) Dataset 2: 22	Dataset 1: 1-Channel Dataset 2: 23-Bipolar Channel	DNN	Dataset 1: 97.5 Dataset 2: 97.63	N/A	N/A	N/A	N/A
(Kunekar et al. 2024)	Epilepsy	500	23-Channel	ML-DL	Training- Validation LR: 66.92–63.9 SVM: 98.09–97.23 kNN: 93.61–91.96 ANN: 98–97 LSTM: 99.88–97.1	N/A	N/A	N/A	True Healthy-False Seizure LR: 75–32 SVM: 98–93 kNN: 95–75 ANN: 98–92 LSTM: 98–93

(Continues)

TABLE A6 | (Continued)

Author	Disease	Subject	Electrodes	Classifier	Accuracy (%)	Sensitivity	Specificity	AUC	F1
(Shen et al. 2024)	Epilepsy	16	22-Bipolar Channel	CNN	97.74	98.90	N/A	N/A	N/A
(Awais et al. 2024)	Epilepsy	Dataset 1:22 Dataset 2:14 Dataset 3:10,874	Dataset 1: 22-Bipolar Channel Dataset 2:34-Channel Dataset 3: 31-Channel	GCN-BRF GCN-LSTM	Dataset 1: 99.61 99.73 Dataset 2: 99.52 99.85 Dataset 3: 99.01 99.40	Dataset 1: 98.86 98.65 Dataset 2: 97 98 Dataset 3: 98.69 98.10	Dataset 1: 98 98 Dataset 2: 99 97 Dataset 3: 98.14 97.25	N/A	N/A
(Kantipudi et al. 2024)	Epilepsy	Dataset 1: 25 Dataset 2: 22	Dataset 1: 100-Channel Dataset 2: 23-Channel	TAENN	Dataset 1: 99.76 Dataset 2: 99.1	Dataset 1: 99.12 Dataset 2: 99	Dataset 1: 99.63 Dataset 2: 98.8	N/A	N/A
(Rivera et al. 2024)	Epilepsy	239	19-Channel	NN	N/A	N/A	N/A	N/A	Network 1D Raw: 61.10 Network 2D Conv: 59.90
(Esmaeilpour et al. 2024)	Epilepsy	24	23-Channel	RF Linear SVM FCL	N/A	86.89 90.34 85.6 Max Voting: 90.76	N/A	N/A	N/A
(Jibon et al. 2024)	Epilepsy	Dataset 1: 22 Dataset 2: 504	Dataset 1: 16-Bipolar Dataset 2: 16-Channel	SGCN-DeepRNN	Dataset 1: 99.007 Dataset 2: 98.08	Dataset 1: 98.06 Dataset 2: 97.88	Dataset 1: 95.025 Dataset 2: 97.95	Dataset 1: 0.97669 Dataset 2: 0.9795	Dataset 1: 96.671 Dataset 2: 97.88
(Liu, Li et al. 2024)	Epilepsy	24	23-Channel	CNN	98.13	98.03	98.23	N/A	N/A
(Jemal et al. 2024)	Epilepsy	Dataset 1: 14 Dataset 2: 23	Dataset 1: 29 Dataset 2: 23	CNN	97.36	98.31	96.97	N/A	N/A
(Wang, Sun et al. 2024)	Epilepsy	Dataset 1: 23 Dataset 2: 6724	Dataset 1: 16-Bipolar Channel Dataset 2: 20-Bipolar Channel	ML-DL	Dataset 1: 98.77 Dataset 2: 98.15	Dataset 1: 97.9 Dataset 2: 97.13	Dataset 1: 98.83 Dataset 2: 98.31	N/A	N/A

TABLE A7 | Autism spectrum disorder related studies.

Author	Disease	Subject	Electrodes	Classifier	Accuracy (%)	Sensitivity	Specificity	AUC	F1
(Tawhid et al. 2021)	Autism Spectrum Disorder	16 (12 ASD/4 HC)	16-Channel	NB LDA RF kNN LR SVM CNN	72.09 89.97 90.59 92.29 94.95 95.25 99.15	66.83 91.54 99.27 90.67 96.99 97.07 99.19	84.67 86.26 70.02 96.13 90.06 90.95 99.04	0.77 0.96 0.97 0.98 0.98 0.98 0.99	78 93 94 94 96 97 100
(Al-Qazzaz et al. 2024)	Autism Spectrum Disorder	40 (30 ASD/10 HC)	19-Channel	CNN	Transfer Learning Models—Hybrid Models MobileNetV2: 81.4–80.8 AlexNet: 80.5–83.9 ResNet18: 74.1–72.3 GoogLeNet: 72.8–74.9 ShuffleNet: 68.9–67.9 Efficient- Netb0: 60.5–68.9	N/A	Transfer Learning Models—Hybrid Models MobileNetV2: 98.2–95.9 AlexNet: 98.2-N/A ResNet18: 95.6- N/A GoogLeNet: 96.7–95.8 ShuffleNet: 95.2–94.3 Efficient- Netb0: 94.9- N/A	—	Transfer Learning Models—Hybrid Models MobileNetV2: 92.7–89.7 AlexNet: 91.9- N/A ResNet18: 86.1- N/A GoogLeNet: 86.2–87.3 ShuffleNet: 83.1–83.7 Efficient- Netb0: 76.9–83.9
(Xu et al. 2024)	Autism Spectrum Disorder	189 (97 ASD/92 Typical Development)	125-Channel	CNN-LSTM	81.08	N/A	N/A	N/A	N/A

TABLE A8 | Other diseases (seizure, stroke, anxiety).

Author	Disease	Subject	Electrodes	Classifier	Accuracy (%)	Sensitivity	Specificity	AUC	F1
(Raeisi et al. 2022)	Seizure	39	19-Channel	GCNN	N/A	N/A	N/A	Mean Squared Coherence: 0.991 Phase-Locking Value: 0.99 Euclidean Distance: 0.973	N/A
(Wang, Yang et al. 2024)	Ischemic Stroke	152	10-Channel	EOSVM	89	N/A	N/A	N/A	89
(Aldayel and Al-Nafjan 2024)	Anxiety	23	14-Channel	kNN LDA SVM RF AdaBoost Bagging Gradient Bagging	Best- kNN:70.09 LDA:75.37 SVM:70.06 RF:87.50 AdaBoost Bagging:78.98 Gradient Bagging:77.87	N/A	N/A	RF PSD-SAM: 0.7914 PSD-HAM: 0.8271 DWT-SAM: 0.8192 DWT-HAM: 0.8781	N/A

Appendix B

Average Results of Different Classifiers' Results on Each Disease

TABLE B1 | Average results of different classifiers' results on depression-related studies.

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	F1 (%)
SVM	84.6	82.44	87.13	0.98	N/A
kNN	78.49	85.52	69.19	0.95	N/A
CT	66.93	N/A	N/A	N/A	N/A
DT	78.64	N/A	N/A	0.94	N/A
NB	83.64	N/A	N/A	0.94	N/A
RF	76.58	N/A	N/A	N/A	N/A
SNN	78.29	N/A	N/A	N/A	N/A
BNMLP	76.92	N/A	N/A	N/A	N/A
DNN	90.55	94.05	88.2	N/A	N/A
GNN	86.7	N/A	N/A	0.91	88.68
SCKA	97.5	96	98.5	N/A	N/A
Regression	N/A	N/A	N/A	0.789	N/A
LSTM-CNN	99.9	100	99.8	N/A	N/A
LSTM-DNN	89.7	N/A	87.5	0.8917	92.1
FLFCFS	92.59	94.74	91.30	0.9243	92.60

TABLE B2 | Average results of different classifiers' results on Parkinson's disease-related studies.

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	F1 (%)
SVM	82.35	76.27	70.01	0.99	73.81
kNN	90.87	94.18	77.14	1	72.11
RF	73.02	N/A	N/A	N/A	N/A
LDA	N/A	N/A	N/A	0.99	N/A
LSTM	99.6	99	100	0.99	99

TABLE B3 | Average results of different classifiers' results on stress-related studies.

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	F1 (%)
NN	80	N/A	N/A	N/A	N/A
SVM	70.5	75.5	68	0.73	N/A
RF	83.78	N/A	N/A	N/A	83.21
DL	86.22	N/A	N/A	0.94	89.8
1D-CNN	95.25	N/A	99.41	N/A	93.98

TABLE B4 | Average results of different classifiers' results on schizophrenia-related studies.

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	F1 (%)
LDA	80.66	78.83	82.48	N/A	N/A
RF	85.07	N/A	76	0.73	N/A
QSVM	100	100	100	N/A	N/A
DT	95	N/A	N/A	N/A	N/A
ET	97.36	N/A	N/A	N/A	N/A

TABLE B5 | Average results of different classifiers' results on Alzheimer's disease-related studies.

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	F1 (%)
SVM	90.14	76.96	88.93	N/A	65
LR	87.5	96	93	0.98	N/A
kNN	86.41	82.58	92.26	N/A	65
RLDA	97.02	94.22	98.49	N/A	N/A
TSKC	98.10	98.02	98.06	N/A	N/A
LDA	88.71	79.95	89.04	N/A	N/A
NB	85.48	85.31	81.8	N/A	N/A
ML-DL	99.85	99.75	100	N/A	99.88
MLP	85	N/A	N/A	N/A	N/A
Boosts	77.67	72.67	81.67	N/A	74.67
DT	73	71	75	N/A	71
CNN	83.28	79.81	87.94	N/A	84.12
DL	98.92	N/A	N/A	N/A	N/A
DBN	94.53	N/A	N/A	N/A	94.1

TABLE B6 | Average results of different classifiers' results on epilepsy-related studies.

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	F1 (%)
DA	88.9	N/A	N/A	N/A	N/A
LSTM	97.41	94.87	99.25	N/A	N/A
CNN	98.42	94.41	98.54	0.88	83.7
SRBC	100	100	100	N/A	N/A
SVM	95.6	97.09	99.27	N/A	N/A
kNN	98.6	N/A	N/A	N/A	N/A
GBM	100	N/A	N/A	N/A	N/A
CNN-LSTM	98	98.3	97.4	0.968	N/A
GNN	97.49	96.81	98.3	N/A	N/A
Deep transformer	85	82	87	N/A	N/A
DNN	97.57	93	94	N/A	N/A
RF	98.3	92.45	98.5	N/A	N/A
MLP	97.3	96	98	N/A	N/A
LR	96.7	95	97.5	N/A	N/A
RUSBoost	86.64	87.04	87.15	0.93	0.93
ML-DL	97.99	97.52	98.57	N/A	0.975
GCN-BRF	99.38	98.18	98.38	N/A	N/A
GCN-LSTM	99.66	98.25	97.93	N/A	N/A
TAENN	99.43	99.06	99.22	N/A	N/A
NN	N/A	N/A	N/A	N/A	60.5
FCL	N/A	85.6	N/A	N/A	N/A
SGCN-DeepRNN	98.54	97.97	96.49	0.978	97.3

TABLE B7 | Average results of different classifiers' results on autism spectrum disorder-related studies.

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	F1 (%)
NB	72.09	66.83	84.67	0.77	78
LDA	89.97	91.54	86.26	0.96	93
RF	90.59	99.27	70.02	0.97	94
KNN	92.29	90.67	96.13	0.98	96
LR	94.95	96.99	90.06	0.98	96
SVM	95.25	97.07	90.95	0.98	97
CNN	75.85	99.19	96.38	0.99	87.41
CNN-LSTM	81.08	N/A	N/A	N/A	N/A

TABLE B8 | Average results of different classifiers' results on other diseases (seizure, ischemic stroke, anxiety) related studies.

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	F1 (%)
GCNN	N/A	N/A	N/A	0.985	N/A
EOSVM	89	N/A	N/A	N/A	89
kNN	70.09	N/A	N/A	N/A	N/A
LDA	75.37	N/A	N/A	N/A	N/A
SVM	70.06	N/A	N/A	N/A	N/A
RF	87.50	N/A	N/A	0.829	N/A
Baggings	78.43	N/A	N/A	N/A	N/A

Appendix C

List of Acronyms

AI—artificial intelligence

BNMLP—batch normalized multi-layer perceptron

BRF—balanced random forest

CT—classification tree

CNN—convolutional neural network

DA—discriminant analysis

DBN—deep belief network

DDPM—denoising diffusion probabilistic model

DeepRNN—deep recurrent neural network

DFT—discrete Fourier transform

DL—deep learning

DNN—deep neural network

DT—decision tree

DWT—discrete wavelet transform

EOSVM—ensemble of support vector machines

ERP—event related potential

ET—extra tree

FCFSFL—functional connection feature selection based on fuzzy label

FCL—fully connected layer

fMRI—functional magnetic resonance imaging

GBD Tree—gradient boosted decision tree

GBM—gradient boosting machine

GCN—graph convolutional network

GCNN—graph convolutional neural network

HCI—human-computer interaction

kNN—k-nearest neighbor

LDA—linear discriminative analysis

LFP—local field potential

LR—logistic regression

ML—machine learning.

MRI—magnetic resonance imaging

NB—Naïve Bayes

NIRS—near infrared spectroscopy

NN—neural network

PCA—principal component analysis

PPMS—primary progressive multiple sclerosis

PRISMA—preferred reporting items for systematic reviews and meta-analyses

RLDA—regularized linear discriminant analysis

RNN—recurrent neural network

ROC—receiver operating characteristic.

RRMS—relapsing-remitting multiple sclerosis

SCKMA—spectral clustering with K means algorithm

SGCN—sequential graph convolutional network

SNN—self-normalizing network

SRC—sparse representation based classification

SVM—support vector machine

TAENN—temporal activation expansive neural network

TSKC—Takagi-Sugeno-Kang classifier

QSVM—quantum support vector machine

XBM—explainable boosting machine

ViT—vision transformer