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TOPICAL REVIEW

Application of Entropy for Automated Detection of Neurological Disorders With Electroencephalogram Signals: A Review of the Last Decade (2012–2022)

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ABSTRACT An automated Neurological Disorder detection system can be considered as a cost-effective and resource efficient tool for medical and healthcare applications. In automated Neurological Disorder detection, electroencephalograms are commonly used, but their low signal intensity and nonlinear features are difficult to analyze visually. A promising approach for processing of electroencephalogram signals is the concept of entropy, a nonlinear signal processing method to measure the chaos in the signal. The aim of this study was to find out the effective entropy measures and the machine learning approaches that produced promising output. Using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines as our method, we have identified 84 studies published between 2012 and 2022 that has investigated epilepsy, Parkinson's disease, autism, Attention Deficit Hyperactive disorder, schizophrenia, Alzheimer's disease, depression, and alcohol use disorder with machine learning approaches considering entropy measures. We show that Support Vector Machines was the most commonly used machine learning model, with consistent performance in most of the studies whereas sample entropy was the most commonly used entropy measure, followed by the approximate entropy. For epilepsy detection, the most used entropy feature was the log energy entropy, whereas the multi-scale entropy was commonly used for Alzheimer's Disease, approximate and sample entropy used for Parkinson's Disease, multi scale and Shannon entropy applied for autism, approximate and Shannon entropy used for attention deficit hyperactive disorder, sample entropy used for depression, approximate and spectral entropy adopted for schizophrenia, and the approximate and sample entropy employed for alcohol use disorder. According to the majority of the studies, there is growing concern about the increase in neuro patients and the heavy resource burden that is associated with their prevalence and diagnosis. Based on these studies, we conclude that Computer-Aided Design systems would be economically advantageous in detecting Neurological Disorders. To incorporate Computer-Aided Design system into the mainstream health care system, future research could focus

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on multi-modal approaches to the disorder and its interpretation and explanation. We believe this is the first review that has combined the electroencephalograms, entropy, and automated detection possibility of the 8 distinct neurological disorders. The study is limited to the papers that used accuracy as their performance evaluation metric. The findings and synthesis of previous studies provides a clear pathway that identifies the entropy approach as a practical solution for automated detection of neurological disorder using electroencephalograms with potential applications in other kinds of signal analysis.

INDEX TERMS Neurological disorder, entropy, automated detection, EEG, artificial intelligence, machine learning.

I. INTRODUCTION

NEUROLOGICAL disorders (ND) are increasingly recognised as a serious worldwide public health concern. These are common problems in health around the world and often remain undetected [1]. One person in every 8 people lives with a mental disorder [2] and one in every five Australians, roughly 4.2 million people, possessed a mental illness in the past 12-months and more than 2 in every 5 Australians between the ages of 16 and 85 years reported having a mental illness at some point in their lives [3]. It is also estimated that one in every five adults is suffering from mental disorder in the USA [4].

Although lower middle-class economies like Bangladesh have registered a comparatively lower (18.75% in adults) percentage of people in 2019 suffering from mental disorder, the number has significantly risen in the post-COVID period with the prevalence of depressive (57.9%), stress (59.7%) and anxiety (33.7%) disorders [5], [6]. In low and lower-middle class economies mental health is often a neglected issue in public health, and data is also often unavailable, incomplete or inaccurate [7], [8]. A primary concern is the timely detection of the mental disorder to benefit the individual, their clinicians and families. The detection of ND is resource-intensive, requiring neurologists and other facilities to dedicate their time and resources to the process. Often, patients have a long waiting time to access services which may not be accessible or affordable [9], which provides a consensus for more cost effective, timely and automated interventions [10].

Previous studies have demonstrated that entropy can be used with automated methods to determine the level of complexity in an electroencephalogram (EEG) signal [11]. Derived from the thermodynamics, entropy, a nonlinear index, is the measure of chaos in a signal [12]. Static or dynamical features of a signal describe the complexity in it. Generally, high entropy means high uncertainty and complexity in a signal. The term ''spectral entropies'' refers to entropies determined from the magnitude components of the signal's power spectrum, whereas ''embedding entropies'' refers to entropies calculated directly from the time series [13], [14], [15]. In this review paper, we have analysed various entropy types used in measuring and assessing EEG signals for automated detection of 8 neurological diseases. More specifically, spectral entropies are determined by analysing the power spectrum of the signal, which is related to the frequency of the signal. Embedding entropies are calculated directly from the time series and disclose details about the signal's temporal variability. In this review paper, these two types of entropies have been analysed and compared in order to assess the EEG signals for automated detection of 8 neurological diseases.

A. MOTIVATION FOR THIS RESEARCH

The purpose of this review is to explore the best performing combination of entropy and ML algorithm for various NDs. To the best of our knowledge, we are the first group to present this information. In this work, we have explored eight neurological disorders including epilepsy, autism, Parkinson's disease (PD), ADHD, schizophrenia (SZ), Alzheimer's disease, depression, and alcohol use disorders. Globally, NDs have become a major health concern because of their rising prevalence and lack of cost-effective treatments. Therefore, researchers are utilizing artificial intelligence and the entropy features of EEG signals to detect the disorders earlier and more effectively. In this study, we highlight possible directions for future research to demonstrate the role of machine learning and AI approaches for detecting ND automatically through the use of EEG signals.

B. STRUCTURE OF THE PAPER

The present study is therefore the first review on entropy and the applications of AI methods for analysing Neurological Disorders (NDs) using the EEG signals. What follows next is a brief account of the various NDs covered in this systematic review followed by the application of popular AI techniques in this growing areas of research interest.

1) EPILEPSY

Epilepsy affects about 50 million people worldwide, with 80 percent of these people living in low- and middle-income countries that are also plagued by endemic diseases like malaria or neurocysticercosis [16]. This disease can affect people of all ages. The greatest prevalence of epilepsy occurs during the first year of life, and it is expected to increase in elderly people over the age of 65 [17]. There is no cure for epilepsy, which is a chronic noncommunicable disease [18]. In epilepsy, abnormal electrical discharges in the brain cause recurrent, and transient, disturbances of perception, which are triggered by excessive cortical neuronal

network synchronisation [19]. Although epilepsy is mostly unknown, prenatal or perinatal brain abnormalities or brain injury due to accidents or genetic factors are believed to be related to its cause [16], [17].

2) AUTISM

As a developmental disability, autism is characterized by restricted, repetitive behavior patterns and activities during the infant and toddler years [20]. In low- and middle-income countries, autism affects one child out of every 100 owing to a lack of information regarding the disease and a lack of detection systems. Children with autism often experience symptoms in childhood, but their needs change as they grow older, which impacts their psychosocial lives [21]. Therefore, awareness and detection systems are essential in order to accurately diagnose and provide appropriate care to individuals with autism.

3) PARKINSON'S DISEASE

Parkinson's disease (PD) affects the motor systems of the brain, which results in slow movement, imbalance walking, tremors, and other symptoms [22]. Additionally, it can cause mental health disorders, sleep disorders, cognitive impairments, and other problems [23]. As Parkinson's disease progresses, some patients develop dementia [24], [25]. There has been an 81% increase in PD diagnosis since 2000 and in 2019 the total number of PD patients is estimated to be over 8.5 million; PD caused 329 000 deaths and is the most fatal ND [26]. This illustrates the severity of the situation and emphasizes the importance of a timely diagnosis and treatment for those who suffer from Parkinson's disease.

4) ADHD

The attention deficit hyperactivity disorder (ADHD) is a ND that influences the academic, social, and everyday lives of the patients [27], [28]. A person with ADHD may have difficulty sustaining focus and attention, controlling impulsivity and hyperactivity, and organizing and completing tasks. These individuals often have difficulty managing everyday tasks, maintaining relationships, and performing well at school. There is a persistent pattern of inattention and hyperactivity-impulsivity in ADHD patients [29], [30]. In most cases, early detection and treatment can greatly benefit patients [31], [32]. To further improve the quality of life of people with ADHD, it is important to raise awareness of the disorder, recognize symptoms early, and provide necessary support and interventions

5) SCHIZOPHRENIA

Patients with schizophrenia experience persistent delusions, hallucinations, disorganized thinking, and highly disorganized behavior [2]. Approximately 1% of the population is affected by this [33] and patients have a life expectancy of 10 to 20 years less than the average [34].

6) ALZHEIMER'S DISEASE

In Alzheimer's disease, memory loss, decreased thinking skills, and difficulty performing simple tasks are common symptoms [35]. As a result, older patients suffer from dementia [36], [37]. Alzheimer's disease is a degenerative disorder, which means it slowly worsens over time (refs). In the course of the disease, memory, thinking, and behavioral functions of the brain are affected. Cognitive abilities, including memory, decision-making, and problem-solving, can also decline as a result of this damage.

7) DEPRESSION

There are several symptoms associated with Major Depressive Disorder or depression, including feeling sad, lacking pleasure and being uninterested in or indifferent to anything for at least two weeks [38]. People who are depressed have poor concentration, low self-esteem, sleep disorders, poor health, and suicidal thoughts. It is estimated that 280 million people worldwide will suffer from depression by 2022, including 23 million children and adolescents. In fact, ref [39] suggests that depression could be a primary disease in high income countries and secondary disease in the world by 2030. In 2020-21, depressive episodes affected 4.6% of Australians, and females (5.3%) were affected more than men (3.8%).

8) ALCOHOL USE DISORDER

The consumption of alcohol habitually causes alcohol use disorder [40]. Alcohol use disorder changes brain functions, which in turn cause problems with mental and behavioral function. Men were twice as likely to abuse alcohol (2.2%) in 2020-21 than women (0.9%) [3]. A EEG signal, however, can help detect an alcoholic state [13], [19]. As a result of brain signals' nonlinearity, it can be difficult for conventional methods to infer useful information about such a state. The use of nonlinear features in EEG signals like entropy may be a viable option for automating the detection of alcohol use disorder. In fact, some studies have used different entropy measures to classify normal versus alcohol use disorder using ML approaches with accuracies ranging from 82.33% to 96.60% [13], [41], [42], [43], [44].

II. REVIEW BACKGROUND

A. DETECTION OF NEUROLOGICAL DISORDERS

Detecting Neurological Disorders (ND) can be accomplished in a variety of ways. Traditional methods include screening questionnaires and surveys [45], [46] which depend mostly on the screening questionnaire, administration procedure, laypersons, response of the patients, which create the probability of inaccuracy [47]. Often, this standard procedure performed by physicians does not have 100% sensitivity, requiring a revised diagnosis [47], [48]. Moreover, this method would be resource heavy and time consuming. While chatbots have found popularity in recent years, the system is not yet standard, since there are differences between experts' decisions and those provided by the app [49]. Neuroimaging techniques can screen brain activities that help to detect neu-

rological diseases with precision [50] as they can assess the brain function in a greater depth [51].

The popular techniques include magnetic resonance imaging (MRI), electroencephalography (EEG), magnetoencephalography (MEG), positron emission tomography (PET), single-photon emission computed tomography (SPECT), and computed tomography (CT) [52]. In addition to creating high resolution images of the brain, MRI is also superior to CT in identifying blood circulation as well as cryptic vasculature anomalies [53]. MEG detects magnetic field created in the brain and able to observe electric flow in the brain [54]. PET or PET-CT is high- imaging tech that was previously used for research due to its high cost and complexity [55]. In addition to MRI or CT, SPECT is another imaging technology that can show blood flow and a superior technology for brain analysis [53].

In spite of the fact that neuroimaging techniques described above perform better for disease detection and clinicians heavily rely on their data, none of them are cost-effective and the infrastructure required is not readily available in many places [56]. As such, EEG, a neuroimaging technology, may be a feasible and economical alternative because of its superior temporal resolution [57]. During an EEG, electrical activity is detected in brain neurons [58]. The tool is widely used by neurologists in various ND detection such as epilepsy, autism, depression, and sleep disorders.

These diseases affect different parts of the brain and use of electroencephalogram (EEG) signals is a way to detect the diseases. The EEG signals are nonlinear, stochastic and appears noise like and hard to detect brain abnormalities through visual analysis of signals [59]. As state-of-the-art detection and consistent procedures are necessary while keeping the affordability in mind and resources requirement to a minimum, computer- aided diagnostic (CAD) can be useful in these cases for clinical decision support systems [60].

The use of various CAD systems that use artificial intelligence (AI) models to detect neuro diseases like epilepsy, autism and depression has shown promising results in recent studies. However, there seems to be a hesitancy to use AI and machine learning in health and medical sectors due to their reliability, accuracy, and variation in results [61]. We examined 84 papers that used CAD and EEG signals to differentiate between abnormal and healthy signals over the last 10 years, in order to determine which AI and machine learning models researchers have used and their accuracy and consistency. The focus of this paper is also primarily on the effect of EEG signals on entropy features. The choice of this method arises from the characteristics of the entropy method which can the capability to analyse EEG as an effective tool for disease detection and the outcomes can be easily translated for physicians' understanding [62].

B. COMPUTER-AIDED DESIGN (CAD) SYSTEM

In general, CAD models based on AI work in six steps as shown in Figure 1. First, the analytics tool can be tasked

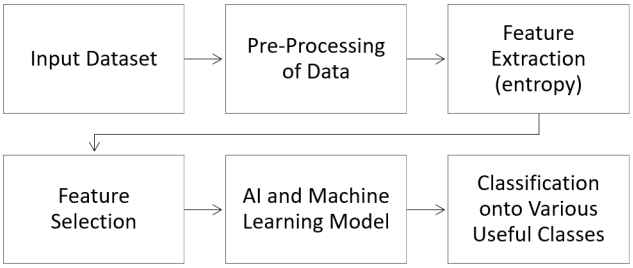

FIGURE 1. Flowchart of Computer Aided Design (CAD) system.

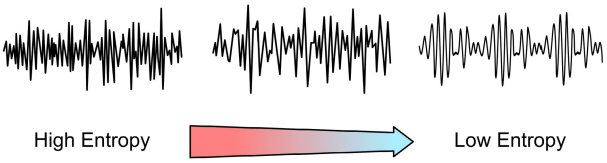

FIGURE 2. Illustration of change in entropy values from high to low entropy for the EEG signals.

to read the file and prepare information for further preprocessing by reading the input dataset. Among the file types considered could be the time series, images, categorical, speech, and texts formats.

The preprocessing step transforms raw data into a format that computers can understand. As a result, redundant, inconsistent or those with significant missing data are removed and the removal of noise also takes place. Following this, the data are then ready for feature extraction which is the third step.

As part of this study, we have collected a large number of techniques for the measures of entropy from raw datasets used in previous research papers. In the subsequent steps, these features could be ranked based on their importance. Once the selected features have been selected, the ML model can then be used to classify them and detect any ND present in patients.

C. ENTROPY

First, we shall briefly describe the concept of entropy that can be applied to the EEG signal analysis for automated detection of neurological disorders before presenting the methodology. Figure 2 demonstrates the high to low entropy features that can be detected in an EEG signal. By examining various types of entropy, which can differ by the amount of instability or irregularity in the signal, we can quantify in a statistical sense the amount of uncertainty and/or randomness present in the EEG patterns, which is expected to reflect the amount of information contained therein. For clinicians and healthcare providers, entropy, as schematized in Figure 2, can provide valuable information regarding the complexity and the irregularities in an EEG signal.

1) APPROXIMATE ENTROPY (ApEn)

The ApEn, as a formulated statistical parameter commonly used to quantify the regularity of an EEG time series, is useful for its ability to handle stochastic components present in these data [63]. Typically, the ApEn measures correlation,

persistence and regularity in data, meaning a low ApEn value indicates a series is repetitive and predictable, thereby showing less uncertainty than a high ApEn value. In a binary system, ApEn can reach a maximum of log2. ApEn is suitable for classifying systems, understanding brain functionality [64], thus is often used in many ND detection systems [13], [14], [42], [65], [66], [67]. ApEn is determined by the below Equation 1 [68].

$$ApEn = ln\frac{C_m(r)}{C_{(m+1)}(r)} \tag{1}$$

where m = pattern length and r = similarity coefficient, $C_m(r)$ = the pattern mean of length m and $C_(m+1)(r)$ = pattern mean of length $m+1$ and $ApEn$ depends on the signal length which works as a drawback when working with shorter signals.

2) SAMPLE ENTROPY (SampEn)

The $SampEn$, as a modified form of ApEn, is used to assess the complexity of any physiological signals, including the EEG. More generally it shows stability reducing the bias of $ApEn$ [68] and is independent of the signal length. Mathematically, $SampEn$ is measured as follows 2:

$$SampEn = -log\frac{A}{B} \tag{2}$$

where A contains the total number of vector pairs of length $m+1$ as described in Equation 2 and B contains total number of vector pairs of length m.

3) SHANNON ENTROPY (H_{sh})

The Shannon entropy, H_{sh} aims to measure the uncertainty of occurrence of certain event in the EEG signal as defined by Shannon [69]. This refers to the foundational entropy of information to measure the probability distribution of EEG data given by:

$$H_{sh} = -\sum_{n=1}^{x} P_n \ log_2 P_n \tag{3}$$

where H_{sh} = probability of occurrence of the feature value, P_n is the n element of the feature, x = total number of features.

4) TSALLIS ENTROPY, H_{ts}

The Tsallis entropy, H_{ts}, presented as a different measure of the uncertainty for the Shannon entropy [70], can deduce the significance of features in the EEG signal and calculates the information gains as follows [71]:

$$H_{te} = \frac{1}{\beta - 1}(1 - \sum_{n=1}^{x} E_n^{\beta}) : \beta \neq 1 \tag{4}$$

where n = number of features, E = probability distribution, β is a real parameter denoted as entropic index [72].

5) RENYI ENTROPY, H_r

As a generalization to Shannon entropy, the Renyi entropy, H_r [73] indicates the spectral complexity of an EEG signal [74].

$$H_{re} = \frac{1}{1-\beta} \ln(\sum_{n=1}^{x} E_n^{\beta}) \ : \beta \neq 1 \tag{5}$$

where E_n = probability of the system, β = order and x = number of phase lattices [75].

6) HIGHER ORDER SPECTRA (*HOS*) ENTROPY

This higher-order spectral entropy, HOS, represents higher-order spectral moments in a random process that capture information due to deviations from normality and subtle variations in the EEG signal.

7) BI SPECTRUM ENTROPY, H_{Bi}

The bi-spectrum represents the third-order moment Fourier transform with two frequencies: $f1$ and $f2$ given by $H(f1, f2) = E[X(f1)X(f2)X * (f1 + f2)]$ where $X(f)$ is the Fourier transform of a given EEG signal $X(nT)$ and the $*$ represents the complex conjugation operator. The Bi spectrum entropy, H_{Bi} [76] is defined as follows:

$$H_{Bi} = -\sum_{n} a_n \log a_n \tag{6}$$

where $a_n = \frac{|H_{Bi}(f_1,f_2)|}{\sum_{\epsilon}|H_{Bi}(f_1,f_2)|}$

.

Therefore the Bi-spectrum squared entropy (H_{Bi-sq}) of an EEG signal is written as follows [76]:

$$H_{Bi-sq} = -\sum_{n} b_n \log b_n \tag{7}$$

$$H_{Bi-cub} = -\sum_{n} c_n \log c_n \tag{8}$$

Here,

$$b_n = \frac{|H_{Bi}(f_1,f_2)|^2}{\sum_{\epsilon}|H_{Bi}(f_1,f_2)|^2} \tag{9}$$

$$c_n = \frac{|H_{Bi}(f_1,f_2)|^3}{\sum_{\epsilon}|H_{Bi}(f_1,f_2)|^3} \tag{10}$$

where ϵ = the region of computation of bi-spectrum.

8) PHASE ENTROPY, H_{ph}

The Phase entropy, H_{ph} [76] was developed from the transfer entropy. This aims to learn about the information transfer between instantaneous phase of any two EEG signals [77].

$$H_{ph} = \sum_{n} a(H_n) \log a(H_n) \tag{11}$$

where $a(H_n) = \frac{1}{N} \sum_{\tau} 1[\phi[B_i(f_1 f_2)] \in H_n]$ and $H_n = \left(\emptyset \left| -\pi + \frac{2\pi n}{A} \leq \emptyset < -\pi + \frac{2\pi(n+1)}{A}\right.\right)$ where $n = 0, 1, \ldots, A-1$, A defines an integer, N indicates the number of samples within τ and $\emptyset$ is the phase angle of the bi-spectrum.

9) WAVELET ENTROPY, H_W

The wavelet entropy, H_w [76], as a compound of wavelet decomposition and entropy, aims to evaluate the intensity of chaos in the EEG signal were H_w is determined as follows:

$$H_w = \sum_{p<0} H_p \ln(H_p) \tag{12}$$

where H_p indicates probability distribution of EEG signal and p signifies the different resolution levels.

10) STEIN'S UNBIASED RISK ESTIMATE, *SURE* ENTROPY H_{SURE}

The Stein's unbiased risk estimate (SURE) entropy [78], [79] signifies the information present in an EEG signal as follows:

$$H_{SURE} = Z - p \; such \; that \; |i_p| \leq \theta + \sum_p min(i_p^2, \theta^2) \tag{13}$$

where Z = length of signal [80], $i_p = p^{th}$ signal sample and θ is always a positive threshold value, typically as 3.

11) RECURRENCE ENTROPY, H_{Re}

The recurrence entropy, H_{Re} calculates the average information present in the EEG signal [81]:

$$H_{Re} = -\sum_{n=n_{min}}^{N} F(n) \ln[F(n)] \tag{14}$$

where N = total sample number, n_{min} = minimal diagonal line length and $F(n)$ = frequency distribution of length n of the diagonal lines.

12) PERMUTATION ENTROPY, H_p

The permutation entropy, H_p aims to estimate the complexity of the EEG signals. It does so by evaluating the coupling between two groups of signals as follows [82]:

$$H_p(x) = -\sum_{n=1}^{m!} H_n \log(H_n) \tag{15}$$

Note that H_p of order $m \geq 2$ indicates that all $p!$ permutations of the selected p denotes the sequence length.

13) LOG ENERGY ENTROPY, H_{log}

The log energy entropy, H_{log} aims to estimate the severity of the complexities within the EEG signal following [78]:

$$H_{log} = \sum_{n=1}^{p} \log(H_n^2) \tag{16}$$

where p and H_n = length of EEG signal and n^{th} EEG signal, respectively.

14) KOLMOGROV-SINAI (K-S) ENTROPY, H_{K-S}

The Kolmogrov-Sinai (K-S) entropy, H_{K-S} computes the variability in the EEG signal as follows [83]:

$$H_{K-S} = \lim_{n\to 0} \lim_{x\to\infty} \frac{1}{\varrho} \frac{F_x(n, N_x)}{F_{x+1}(n, N_{x+1})} \tag{17}$$

where $F_x(n, N_x) = \frac{2}{N_x(N_x-1)} \sum_{i=1}^{N_x} \sum_{j=1, j\neq 1}^{N_x} H(n - p_i - p_j)$ where $F_x(n, N_x)$ signifies the correlation function, p_i and p_j are points on the trajectory of phase space defined by n around a reference point, H represents the Heaviside function and $N_x(N_x - 1)\varrho$ indicates the number of points in the multi-dimensional state space.

15) MODIFIED MULTI-SCALE ENTROPY, H_{mms}

The modified multi-scale entropy (H_{mms}, in accordance with [84] and [85], aims to combine two methods based on different time scales using a moving-averaging approach and sample entropy with a time delay t to the moving-average time series. The H_{mms} identifies a pattern in the EEG signal based on the regularity as follows:

$$a_p^l = \frac{1}{l} \sum_{n=x}^{p+l-1} H_n \; 1 \leq p \leq 1 - l + 1 \tag{18}$$

and

$$H_{mms} = H_s(l, h) \tag{19}$$

where a^l = moving-average time series with a scale factor of l and h = pre-defined threshold.

16) FUZZY ENTROPY, H_f

The fuzzy entropy, H_f detects the similarities in EEG signal [86]. This is based fuzzy set theory [87] whereby the term H_f is expressed as:

$$\phi^l(K, w) = \frac{1}{Q-m} \sum_{x=1}^{Q-m} \frac{1}{Q-m-1} \left[\sum_{y=1, y\neq x}^{Q-m} (Q_{xy}^m) \right] \tag{20}$$

and

$$H_f = \ln\left[\phi^m(K, w)\right] - \ln\left[\phi^{m+1}(K, w)\right] \tag{21}$$

where m = length of the EEG signal.

It should be noted that a degree of similarity (Q_{xy}^m) exists between the two sequences (x^{th} and y^{th}) obtained by ($Q_{xy}^l = \mu(Q_{xy}^m, K, w)$ where μ, K and w are the fuzzy function, gradient, and the width of the fuzzy similarity threshold, respectively and Q is the total number of EEG samples [88].

III. MATERIALS AND METHOD

Based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), a systematic search of all relevant resources was conducted retrospectively through four primary databases (i.e., Google Scholar, Scopus, PubMed, and Mendeley). These databases were specifically chosen as they contained a wealth of quality research papers

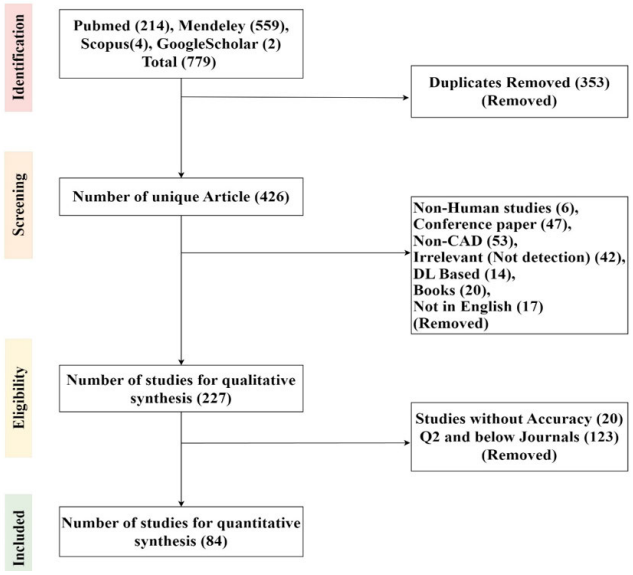

FIGURE 3. Flow diagram of PRISMA approach used for this systematic review.

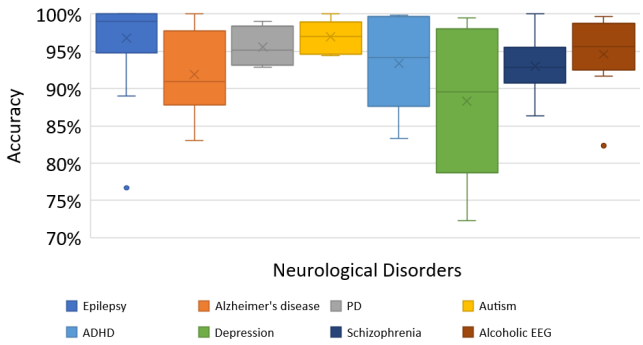

FIGURE 4. Whisker plot representation showing the highest accuracy for various NDs.

on this subject. The topic-related specific Boolean strings, as shown in Table 1, were used to generate the queries for the databases.

These searches yielded 779 key studies; two came from Google Scholar, four from Scopus, 214 from PubMed, and 559 from Mendeley database, and the timeline of research was set from 2012 to June 2022. Our first search found 353 duplicate studies, which were removed. Further assessment resulted in the exclusion of 6 non-human studies, 47 conference papers to minimize the number of papers, 53 non-CAD papers, 42 not related to detection, 14 DL papers, 20 books, and 17 non-English papers. Furthermore, twenty papers without any reference to accuracy in their assessment criteria were removed and we selected only papers in the top 25% (or quartile 1) of the disciplines relevant to this research. In the end, 84 research studies that did not provide model accuracy results were eliminated.

Figure 3 shows the detailed article selection procedure according to PRISMA guidelines.

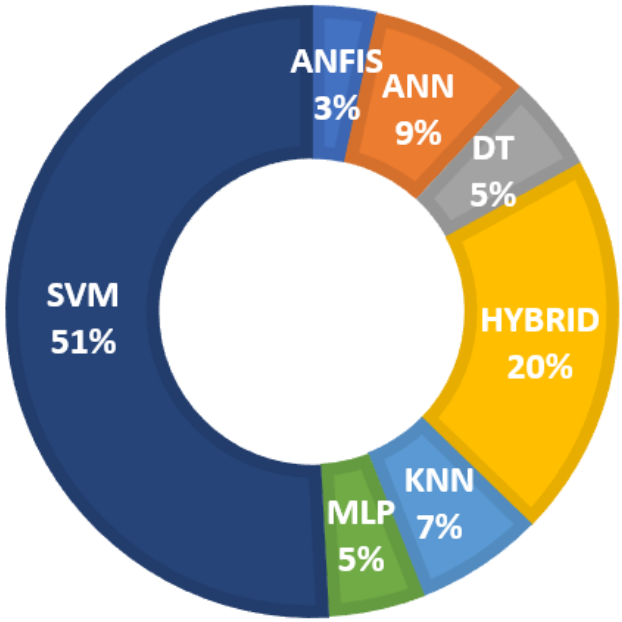

FIGURE 5. Pie chart showing (%) of ML models used for automated detection of NDs.

A. RESULTS, ANALYSIS, SYNTHESIS AND INTERPRETATION

In this study, we reviewed 84 papers and their use of various ML models to detect ND. Overall, the accuracy of the models used in all these papers showed promising performance, as shown in the box and whiskers plot in Figure 4. Considering these results, it can be concluded that the average accuracy for all papers was 93.66 %. Out of 84 papers, about 36% (30) used a support vector machine (SVM) as their classifier to detect ND diseases (Figure 5). Although the results varied between 72.25% to 100% accuracy, the discussed 8 ND (see Table 4 to Table 11 in Appendix II) achieved superior performance with SVM: epilepsy (100%) [89], Alzheimer's (100%) [90], autism (100%) [91], ADHD (99.58%) [92], PD(99%) [93], SZ(93%) [94], depression (90.26%) [95] and alcoholism (95.80%) [96].

It is noticeable that 14 papers have used a hybrid approach where multiple ML classifiers are used to devise the model, followed by an ANN model in 5, a KNN model in 4, an MLP model and a DT model in 3 and ANFIS in 2 studies, respectively (Figure 5 and Figure 6) with an average accuracy of hybrid approaches to be 97.67%. Interestingly, in 8 of the 14 studies that involved hybrid models, the SVM model was a common approach where results varied from 92.68 to 100% (Figure 6).

The pie chart representation (Figure 7) shows that 9 of 33 studies (see Table 4 in Appendix II) on epilepsy were tested for accuracy, with a range of 89.80% to 100% and a mean of 96.33% (Figure 8). It is noteworthy that the SVM model appears to be one of the most popular ML algorithms used for classification problems. One of the versions of SVM, the least-square support vector machine (LS-SVM), has been used in four of epilepsy studies [89], [97], [98],

TABLE 1. Details of Boolean strings and number of selected papers from various databases.

Boolean [Title/Abstract]	AND Disease Title	Database				Total No. of Studies
		Scopus	*PubMed*	*Mendeley*	*Google Scholar*	
entropy + machine learning + EEG signals						
OR						
entropy + detection + EEG signals	Parkinson's disease	2	14	9	2	27
OR						
entropy + automated detection + EEG signals						
	Alcohol use disorder	0	0	20	0	20
	Depression	0	17	22	0	39
	Autism	0	14	24	0	38
	Epilepsy	0	124	426	0	550
	Schizophrenia	1	12	17	0	30
	Alzheimer's disease	0	26	31	0	57

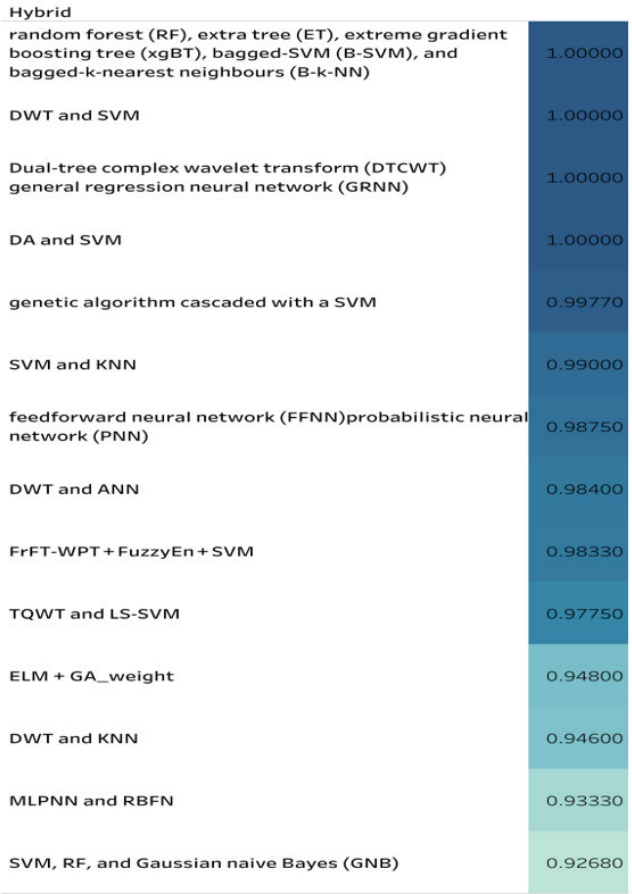

FIGURE 6. Graphical representation of average accuracies obtained for various combination of entropy and ML models for automated detection of NDs.

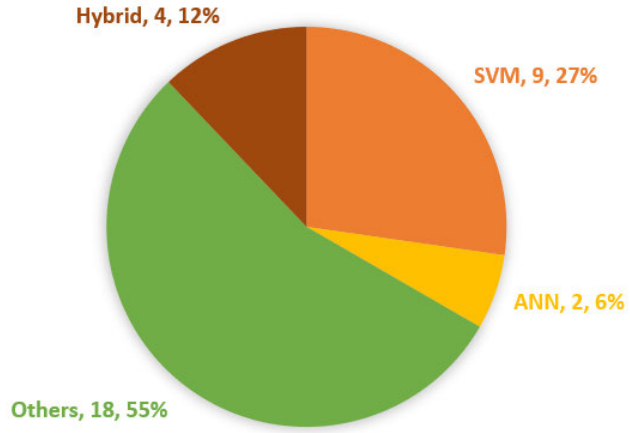

FIGURE 7. Pie chart showing the contribution(%) of various classifiers in automated epilepsy detection.

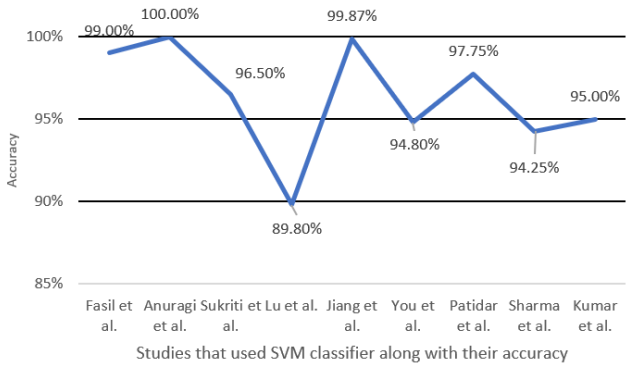

FIGURE 8. Highest accuracy values obtained by various authors for automated epilepsy detection using SVM classifier.

[99]. In general, the LS-SVM model is suitable for processing large amounts of data while reducing computational time as it changes the quadratic computing problem approach arising from the limitation of traditional SVM into solving a linear equation problem [100], [101].

In the case of Alzheimer's studies (see Table 7), one-third of the researchers used SVM and received a 100% classification accuracy as shown in Figure 9 [90]. Another study [102] exhibits 100% specificity, 87.8% sensitivity and 91.6% accuracy through SVM and epoch-based entropy analysis. Two-thirds of ADHD-based studies (see Table 8 in Appendix II) have used an SVM model whereas three of them used an SVM model with a kernel radial basis function (SVM-RBF) (Figure 10). Notanlyt, the RBF is a kernel function that maps data into higher dimensional space which otherwise will be difficult to classify with any linear model [103], [104].

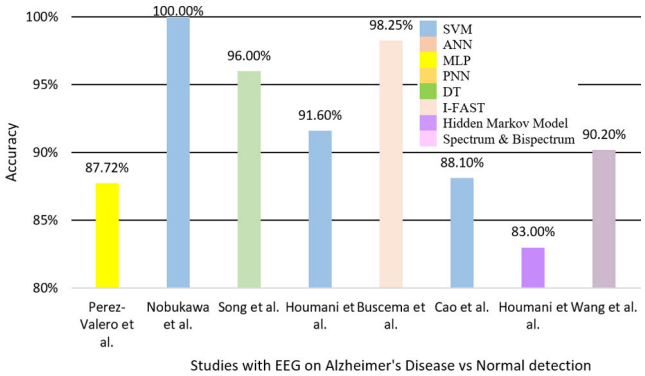

FIGURE 9. Bar- chart showing the highest accuracy obtained by various authors for automated detection of Alzheimer's disease.

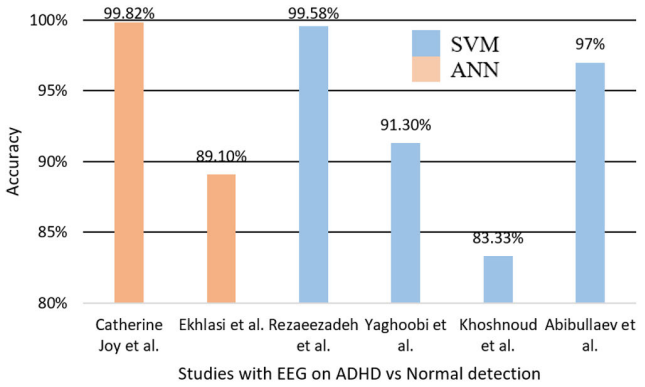

FIGURE 10. Bar- chart showing the highest accuracy obtained by various authors for automated detection of ADHD.

TABLE 2. Predominant entropy measures and their occurrence in various NDs.

Disease	Most Used Entropy	Occurrence
Epilepsy	Log Energy Entropy	10
Alzheimer's Disease	Multi Scale Entropy	3
PD	Approximate and Sample entropy	2 each
Autism	Multi Scale and Shannon Entropy	2 each
ADHD	Approximate and Shannon Entropy	2 each
Depression	Sample entropy	5
Schizophrenia	Approximate and Spectral Entropy	4
Alcohol use disorder	Approximate and Sample Entropy	3 each

We wish to clarify that this review study has focused mainly on the entropy features extracted from EEG signals used to detect ND. We have therefore observed at least 33 types of entropy used in these previous studies. Among these studies, the sample entropy appeared 24 times, followed by he approximate entropy (15), Shannon entropy (14), log energy entropy (12), spectral entropy (11), and the fuzzy entropy (8).

Figure 11 illustrates a doughnut diagram of the entropy features used in the study. Table 2 and Figure 12 shows the most commonly used entropy measures by the disease type.

IV. DISCUSSION

This review is the first attempt to identify entropy features and ML approaches that can accurately detect ND. According to Figure 13, the use of machine learning approaches for year-wise detection of the ND diseases has gradually increased from 2013 to 2017, albeit with a drop in 2018. This is likely

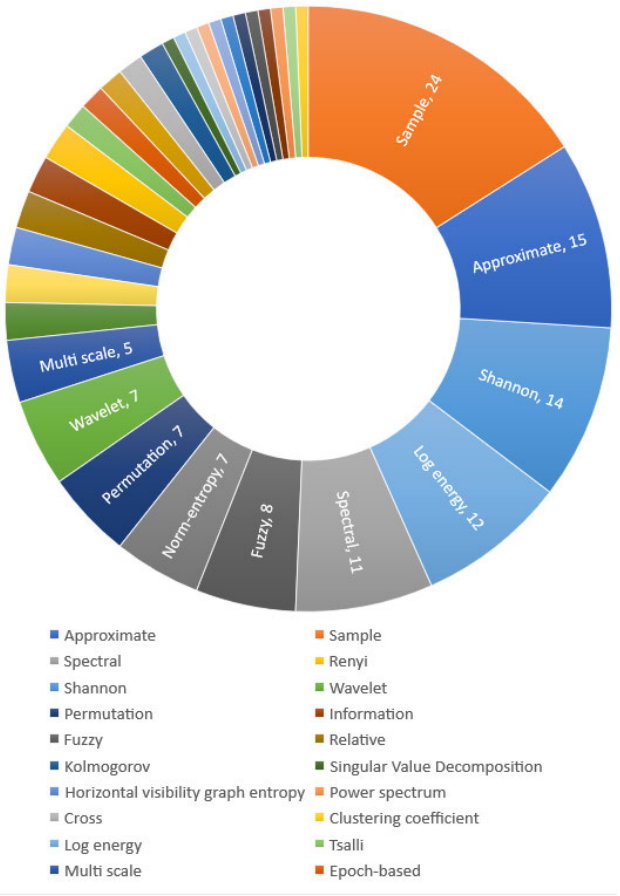

FIGURE 11. Doughnut diagram showing the number of entropy features used in various NDs.

due to the increasing popularity of deep learning (DL) algorithms in disease detection [105].

In 2020, the number of papers peaked once again, which may explain the increase in mental illness concern among COVID patients. As we looked forward to 2021, we saw a decrease in the number. It is noteworthy that the research papers for this study were chosen in June 2022 which includes the 2019 to 2022 period when the world has experienced the COVID-19 effect. As a result of this, there were mental illness and depression type repercussions during the COVID period providing us an opportunity to conduct research to identify the impacts of COVID-19 on mental illnesses [106] as well as depression [107].

Figure 14 illustrates the annual totals of the NDs. Regardless of the year-wise study numbers, the total number epilepsy papers were relatively high, covering 39% of the total studied papers, as also shown in Figure 15. It is not surprising considering around 50 million people worldwide suffer from this disease [108]. Around 14% of studies were on depression detection using ML approaches.

Papers specifically on depression detection (see Table 9 in Appendix II) with entropy features and ML approach was common in all the years from 2012 onwards but hit a peak in 2020 with 3 papers. Alcohol use disorder (see Table 11 in

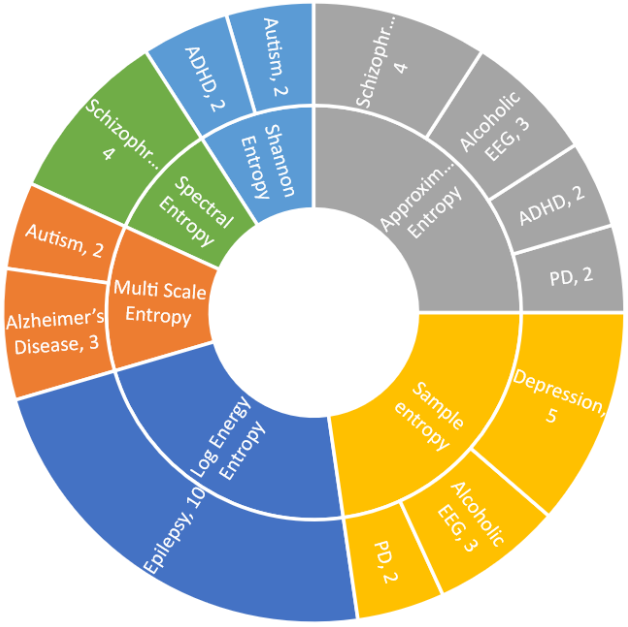

FIGURE 12. A sunburst diagram representing most used entropy measures and their occurrence for various NDs.

Appendix II) and Alzheimer's disease each covered 10% of the study. Interesting, the number of papers on alcohol use disorder was consistent until 2018 and dropped afterwards. In contrast, the number of studies on Alzheimer's disease became consistent after 2018.

It is notable that there are numerous ways disease detection may take place. Some diseases are detected via brain analysis using neuroimaging technologies (discussed previously such as SPECT, PET, CT, MRI, EEG, etc), motor symptoms (speech analysis, hand writing, hand movement), demographics like age, pathological changes, etc, which are not part of these studies.

Based on the synthesis of our results, we now outline the key challenges and future research direction in respect to automated detection of NDs using ML and AI approaches.

V. PRACTICAL CHALLENGES OF AI TECHNIQUES AND FUTURE DIRECTIONS

In accordance with our findings, the DL approaches have become popular after 2018 [105]. The main difference between a ML and a DL approach is that DL allows a researcher to use large amounts of data easily, which often requires less processing on their part. This makes it a popular choice for modelling, which is also providing promising results in terms of accuracy, sensitivity, specificity, area under curve, etc. On the contrary, ML techniques cannot handle big amount of data and also requires heavy preprocessing of the data. This makes DL approaches more favourable.

New DL models such as convolutional Neural network (CNN), long short-term memory (LSTM), Attention models, generative adversarial network (GAN), etc. have already shown good performance in multiple disciplines but demand bigger dataset.

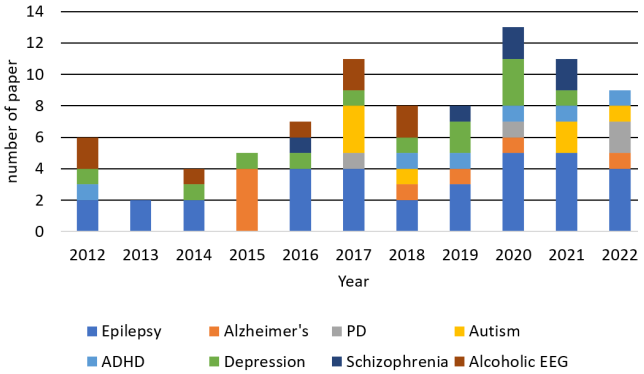

FIGURE 13. Bar-chart showing the number of ML approaches with entropies yearly from 2012 to 2022 for various NDs.

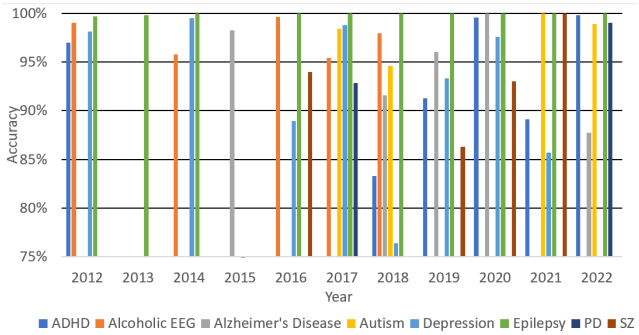

FIGURE 14. Bar-chart showing the highest accuracy obtained yearly from 2012 to 20222 for various NDs.

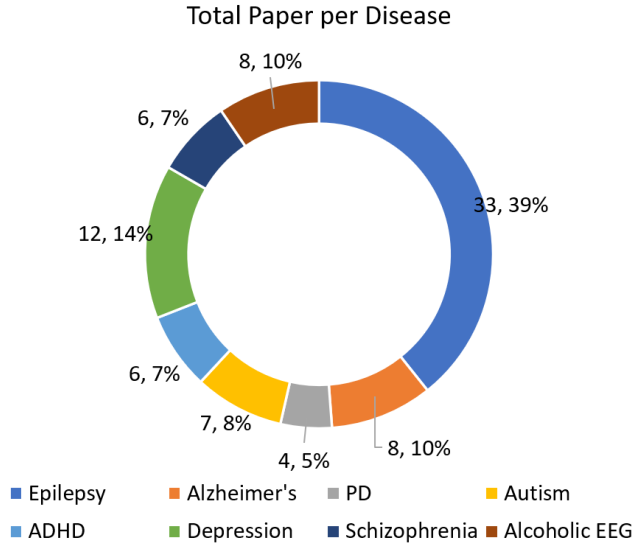

FIGURE 15. Doughnut diagram showing the (%) of studies conducted on various NDs.

Despite this, the healthcare professionals are still not embracing this technological advancement for many justifiable reasons [109], [110]. One major reason is the lack of interpretability and explainability of any AI model [111].

In general, AI is thought to be a black-box approach [112] without providing a clear explanation to why a model classifies a given data as a certain type [113]. While healthcare

systems require precise explanation and evidence-based diagnosis, this contradicts how AI approaches work [109], [114]. To avail this arena to healthcare experts, AI interpretability and explainability should ideally be part of further studies.

In order to bridge the gap between AI and their practical use and opinion among healthcare experts, further studies should focus on increasing the *interpretability and the explainability of AI models* [111], [115], enabling a more transparent approach that provides evidence-based diagnoses. For future research initiatives in this area of health and medical informatics, developing interpretable, explainable, and ethical AI methods for diagnostic screening is paramount [116]. Thus, AI-based diagnosis/screening may be more widely adopted in the healthcare system as a result of greater trust and acceptance by the healthcare community and those diagnosed with the disorder. Additionally, AI approaches are not recognized as standard procedures for diagnosing diseases by the current diagnostic processes.

According to policy-making organizations and medical boards such as the American Psychological Association (APA) and the UK Parkinson's Disease Brain Bank (UKPDSBB), physicians must follow the assessment criteria. Since these organizations, and the others, have not yet validated any such models, AI models are not included in the diagnostic tools. Proper education, preparation and understanding of AI can help the policy-makers and physicians to be more familiar with the innovation [117], [118]. Most diseases discussed in this study, however, have multiple types and criteria for each type to qualify and classify a person as a patient.

Current studies, however, whether ML or DL, have not incorporated such types of variations. Past studies have often aimed on single modality rather than a multi-modal approach that are common for these diseases [119], which would sensible and effective ways to use the models for clinical use [120]. In order to obtain regulatory approval from the governing bodies, it is necessary to use multimodal approaches that are standard in diagnosing these disorders. To obtain regulatory approval from governing bodies and ensure effective clinical use, future research should take a multi-modal disease detection approach.

Both ML and DL are data-driven approaches, so data availability [121] could also an issue when making multimodal CAD tools. The process of obtaining patient data for further research and trials could be relatively complex and time-consuming, due to growing concerns about data safety and risk, which often requires multiple ethics approvals. This could hinder the development of an effective CAD tool. Public datasets, although, being currently available, could be insufficient and have a limited amount of data. Currently, patient data needs to be manually labelled by the experts before being used by AI techniques to train the models, which could also present challenges in terms of reliability of those manually labelled datasets.

Another issue is the availability of systematic long-term storage systems of data, which are relatively scarce due to the time constraints of creating such records as well as financial constraints, and a lack of funds to maintain the storage system. Ideally, a bigger, reliable data set would make a better model when using a data-driven approach, since the model needs to be trained on more data to analyse large amounts of patterns. Another matter of consideration is that it is currently not possible to provide detailed information, such as physical or behavioral diagnoses, based on the available dataset. Having a dataset with patient age and other vitals and periodically updating those data along with the EEG signal information will help understand the trend of disorder since many of the neurological disorders are linked to one another, such as many Parkinson's disease and Alzheimer's disease patients develop dementia as they age [122], [123].

According to our findings, there is no dataset available on infants and young children. The development of such a dataset with information about demographics such as age, size, variation, and the availability of the dataset will contribute to CAD tools that are accurate and efficient. The datasets could be used to create more accurate computer-aided design (CAD) tools for pediatric prosthetics and other medical devices. Consequently, young individuals will be able to receive better diagnosis and treatment, and devices can be produced more efficiently.

CAD tools can be used to bring many diseases under one umbrella and develop a universal diagnostic and detection tool for healthcare systems. In comparison to other neuroimaging techniques, EEG provides more accurate results and in developing countries as well as developed ones, there is already an infrastructure for EEG analysis. In addition to standardizing the healthcare system, this will enable economies of scale since data scarcity will be addressed.

Figure 16 shows a simple flowchart of the prescribed cloud system designed for automated detection of neurological diseases. It is noticeable that by using portable devices, the EEG data can be transferred to a cloud database for cloud computing purposes using AI techniques, which can be accessed easily by neurologists and healthcare professionals [105]. This approach allows the development of a large database of diverse information using a multimodal approach. In addition to improving the quality of patient care, this multidimensional approach can allow for more accurate diagnoses and better treatments. While an automated detection system may lead to changing roles or responsibilities of healthcare experts [124], the proposed task-oriented training of AI models and a future change management system can help ease its transition into healthcare practice and subsequent adoption by clinicians.

VI. LIMITATION OF THE REVIEW STUDY

1) This review study has focused on several key research works that have used entropy features of EEG signals for neurological disease detection. This study, however, has identified some of the other methods such as the

TABLE 3. List of acronyms used in this review paper.

ADHD	Attention deficit hyperactivity disorder
AI	Artificial Intelligence
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
ApEn	Approximate Entropy
ASD	Autism or Autism Spectrum Disorder
AUC	Area Under the Curve
B-k-NN	Bagged k Nearest Neighbor
B-SVM	Bagged Support Vector Machine
CAD	Computer aided design
CT	Computed Tomography
DA	Discriminant Analysis
DL	Deep Learning
DT	Decision Tree
DTCWT	Dual-Tree Complex Wavelet Transform
DWT	Discrete Wavelet Transformation
ECG	Electrocardiogram
EEG	Electroencephalogram
ELM	Extreme Learning Machine
ET	Extra-Tree
FFNN	Feed Forward Neural Network
FrFT	Fractional Fourier transform
GA	Genetic Algorithm
GNB	Gaussian Naïve Bayes
GRNN	General Regression Neural Network
HB_i	Bi spectrum entropy
HB_{i-cub}	Bi-spectrum cubic entropy
HB_{i-sq}	Bi-spectrum squared entropy
H_f	Fuzzy entropy
H_{log}	Log energy entropy
H_{mms}	Modified multi-scale entropy
HOS	Higher order spectra entropy
H_p	Permutation entropy
H_{ph}	Phase entropy
H_r	Renyi entropy
HR_e	Recurrence entropy
H_{sh}	Shannon entropy
H_{ts}	Tsallis entropy
H_w	Wavelet entropy
KNN	k-Nearest Neighbor
KS	Kolmogrov-Sinai (K-S) entropy
LS-SVM	Least Square Support Vector Machine
MEG	Magnetoencephalography
ML	machine learning
MLP	Multilayer perceptron
MLPNN	multi layered perceptron neural network
MRI	Magnetic Resonance Imaging
ND	Neurological Disease
PD	Parkinson's disease
PET	Positron Emission Tomography
PNN	Probabilistic Neural Network
PRSIMA	Preferred Reporting Items for Systematic Reviews & Meta-analyses
RBFN	Radial basis function network
RF	Random Forest
SampEn	Sample Entropy
SPECT	Single-Photon Emission Computed Tomography
SURE	Stein's unbiased risk estimate
SVM	Support Vector Machine
SVM-RBF	Support Vector Machine Radial Basis Function
SZ	Schizophrenia
TQWT	tunable-Q wavelet transform
WPT	Wavelet packet transform
WT	Wavelet Transform
XGBT	Extreme Gradient Boosting Tree

neuro-imaging approach that can be used for disease detection. We also note that ECG signals, for example, could be an affordable and efficient way toward the ND detection system, especially when it comes to epilepsy and ADHD [56], [125], [126] and ADHD detection [127]. In general, the use of an ECG signal could be a viable option for ND detection due to the brain-heart autonomic interactions that exist whereby the noise can be filtered out in a greater detail and the ECG signals can be down-sampled to reduce the

TABLE 4. List of papers reviewed in epilepsy studies.

Year	Authors	Entropy Type	Classifier Type	Accuracy
2022	[128]	Improved SampEn	Variational Mode Decomposition	97.78
2022	[65]	ApEn, and SampEn	SVM	99
2022	[89]	Hlog and norm-entropy	Hybrid (RF, ET, xgBT, B-SVM, and B-k-NN)	100
2022	[129]	SE	Deep Maxout network	93.6
2021	[130]	MDE and RCMDE	SVM	96.5
2021	[89]	Hlog and norm-entropy	LS-SVM, SVM, k-NN, EBT	100
2021	[131]	SampEn	SVM	89.8
2021	[132]	Entropy	ANFIS, NN	99.7
2021	[133]	FDispEn, Hp and Hsh	SVM	99
2020	[134]	ApEn, SampEn, Hp	SCANN	98.5
2020	[99]	Hlog and fDistEn	LS-SVM	94.8
2020	[135]	Hlog, Hsh, SURE	ANN	100- KITS DB 97.4- TUH DB
2020	[136]	Hlog, Hsh, Norm, and SURE	DWT	100
2020	[137]	Hf and Hlog	SVM	99.87
2019	[138]	Hf	hybrid	98.33
2019	[139]	Normalized Hsh , Hlog, Norm	RF	99.4
2019	[140]	Sigmoid	DWT and SVM	100
2018	[141]	Hf and DistEn	QD	91
2018	[142]	Hlog, Norm	MLP	100
2017	[98]	Hw	LS–SVM	94.25
2017	[143]	Cross	Hybid ANNs	99.9
2017	[97]	Kraskov	TQWT and LS-SVM	97.75
2017	[144]	clustering coefficient	adaptive optimal kernel time-frequency representation and visibility graph	100
2016	[145]	Hlog, Hsh, Norm	Gaussian process classifier	89
2016	[146]	Hsh	DTCWT, GRNN	100
2016	[145]	Hlog, Hsh, Norm	k-means classifier	94.6
2016	[147]	Hp, SampEn	DA	76.7
2014	[148]	SampEn	FWHVA	100
2014	[149]	fuzzy approximate	SVMs	95
2013	[150]	SampEn	Hybrid (GA cascaded with a SVM and post-classification spike matching)	99.77
2013	[151]	Hp , SampEn	ELM and GA	94.2
2012	[152]	SE	C4.5 DT	95.33
2012	[14]	ApEn and SampEn	FSC	99.7

TABLE 5. List of papers reviewed in Parkinson's disease studies.

Year	Authors	Entropy Type	Classifier Type	Accuracy
2022	[153]	approximate entropy	SVM	96.40%
2022	[93]	log energy entropy	SVM, k-nearest neighbor	99%. On-medication PD: 95-98%
2020	[154]	Feature extraction: AE, TE, FE, SE, ShE	probabilistic neural network	93.88%
2017	[155]	sample entropy (SampEn)	optimal center constructive covering (O_CCA)	92.86%

TABLE 6. List of papers reviewed in Autism studies.

Year	Authors	Entropy Type	Classifier Type	Accuracy
2022	[156]	MSE and SE	SCG-NN	98.9% and 95.0%
2021	[91]	SampEn	DA, SVM	100%
2021	[157]	Information	GCN	95%
2018	[158]	Hsh	Hybrid (DWT, KNN)	94.60%
2017	[159]	cross correntropy, SURE, and Hsh	LS-SVM	94.41%
2017	[160]	Hsh	DWT and ANN	98.40%
2017	[161]	MSE	DT	97%

TABLE 7. List of papers reviewed in Alzheimer's studies.

Year	Authors	Entropy Type	Classifier Type	Accuracy
2022	[125]	spectral entropy	multi-layer perceptron	87.72
2020	[90]	multi-scale entropy	SVM	100
2019	[162]	generalized composite multiscale entropy	Functional network analysis and seed analysis	96
2018	[102]	epoch-based entropy	SVM	91.6
2015	[163]	multi scale entropy	implicit function as squashing time (I-FAST)	98.25
2015	[164]	fuzzy entropy	SVM	88.1
2015	[165]	Epoch-based entropy	Hidden Markov Model	83
2015	[166]	spectral entropy	spectrum and bispectrum	90.2

computational costs. These improvements can make ECG an excellent competitor to the conventional EEG signal analysis for automated ND detection [127].

2) A key criterion for choosing the studies for this review was their model accuracy. As a result of this screening process, numerous studies were removed from our

TABLE 8. List of papers reviewed in ADHD studies.

Year	Authors	Entropy Type	Classifier Type	Accuracy
2022	[80]	Hp	ANN	99.82%
2021	[77]	dPTE	Multilayer ANN	89.10%
2020	[92]	Combining: Hsh, (SampEn, DispEn and MSE	SVM-RBF	99.58%
2019	[167]	ApEn	SVM-RBF	91.30%
2018	[168]	ApEn	SVM-RBF	83.33%
2012	[169]	Hsh, conditional entropy	SVM	97%

TABLE 9. List of papers reviewed in Depression studies.

Year	Authors	Entropy Type	Classifier Type	Accuracy
2021	[170]	Differential entropy	SVM	84% and 85.7%
2020	[171]	Hr	KNN	72.25%
2020	[172]	SampEn	MLP, Logistic, SVM, DT, RF, Naïve Bayes	90.24 to 97.56%
2020	[95]	SampEn	SVM kernels	90.26% (depression); 75.31% (severity)
2019	[173]	Hw and relative Hw	MLPNN and RBFN	93.33%
2019	[174]	information entropy, SampEn and ApEn	SVM and NB	mean = 84.2%, high = 86.3%
2018	[175]	Hsh, KS and power spectrum entropy	DT	76.40%
2017	[176]	Hw	FFNN and PNN	99%
2016	[177]	Hw	SVM-RBF	88.92%
2015	[19]	SampEn	SVM	72.25%
2014	[66]	ApEn, SampEn, Hr and bispectral phase	PNN, SVM, DT, k-NN, NB, GMM and FSC	99.50%
2012	[178]	Relative Hw	ANN	98.11%

TABLE 10. List of papers reviewed in Schizophrenia studies.

Year	Authors	Entropy Type	Classifier Type	Accuracy
2021	[67]	ApEn, SampEn, SE	ANFIS, SVM, ANN	100 ANFIS, 98.89 SVM, 95.59% ANN
2021	[179]	symbolic transfer entropy	SVM, RF, GNB	92.68%
2020	[180]	SampEn	SVM-RBF	92.17%
2020	[94]	ApEn, SampEn, Hp, SE, Singular Value Decomposition entropy	SVM-RBF	93%
2019	[174]	information entropy, ApEn, SampEn	SVM	86.30%
2016	[181]	SE and Hr, ApEn	k-NN	94%

TABLE 11. List of papers reviewed in alcohol use disorder studies.

Year	Authors	Entropy Type	Classifier Type	Accuracy
2018	[44]	Entropy and negentropy	ELM	97.92%
2018	[42]	SampEn, ApEn	SVM (Quadratic)	95%
2017	[182]	SampEn, ApEn, Hp, Hsh, Hr, Hts, Hf, Hf, KS, Hmms	SVM	95.41%
2018	[41]	Relative entropy	KNN	82.33%
2016	[43]	SE	MLP, k-NN, Independent Component Analysis (ICA)	99.60%
2014	[96]	HVGE	SVM	95.80%
2012	[13]	ApEn, SampEn	SVM	91.70%
2012	[183]	SE	SVM	MLP-BP-acc-90 PNN acc- 99 SVM acc- 92%

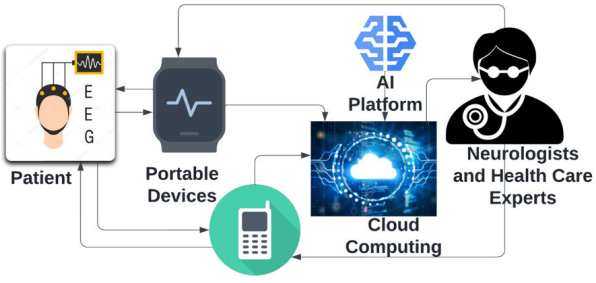

FIGURE 16. Snapshot of the proposed cloud-based automated ND diagnosis and monitoring.

analysis. It would have been worthwhile to use other metrics such as specificity, sensitivity, and area under the curve (AUC) to measure AI and ML model accuracy in these studies. As a result, the research was limited by using only accuracy as a key criterion to choose a paper for analysis. In order to rectify this problem, future research could include several other measures.

3) Both public and private datasets from a variety of sources have been used in studies. Because the models are trained using different datasets, it is difficult to determine which model is the best performing model. Therefore, a future research could utilise a single big dataset that is sufficiently large enough to provide a variety of features, although developing such datasets could also be a challenging endeavour.

VII. CONCLUSION

A total of 84 studies were reviewed from 2012 to 2022 that used machine learning techniques and entropy features from EEG signals to detect 8 neurological disorders. In cases of epilepsy, Alzheimer's, and autism, most studies achieved 100% accuracy, while the highest accuracy for other disorders reached over 95%. Approximately 36% of studies have used SVMs, and 17% used hybrid approaches with 57% of those studies utilizing SVM models.

Our review found that a possible lack of consistency in the model's performance, interpretability, and explainability issues have prevented CAD tools from being accepted and incorporated into clinical screening systems. In addition, most studies used single modalities instead of multi-modal approaches based on diagnosis criteria, which could interfere with the use of CAD tools to support end users.

There was a clear concern about the growing number of ND individuals, the scarcity of resources like neurologists, the infrastructure, and the time-sensitivity of detecting the disorder in all studies. It is therefore imperative to incorporate CAD tools into ND screening in order to reduce the burden on health care professionals, as well as improve AI models with more data over time.

Finally, this research recommends that the use of machine learning AI technology could help detect early signs of NDs much more quickly and accurately than the traditional methods. In addition to improving the patient outcomes, reducing the time and the resources needed to diagnose can also ease the burden on health care professionals. Furthermore, AI models can successively improve over time with more datasets added to retrain the models, making them even more accurate and reliable for real-life applications.

APPENDIX I. LIST OF ACRONYMS

Table 3 shows the list of various acronyms used in this review study.

APPENDIX II. SUMMARY OF PREVIOUS RESEARCH

Tables 4-11 show the full set of supplementary results of the systematic review. The year of publication, authors, entropy type investigated in the study, as well as the machine learning classifier type and accuracy are also shown. The results shown here are derived from 779 key research works from Google Scholar, Scopus, PubMed, and Mendeley databases within the period 2012 to June 2022.

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REFERENCES

[1] M. R. A. Manaf, M. Mustafa, M. R. A. Rahman, K. H. Yusof, and N. A. A. Aziz, "Factors influencing the prevalence of mental health problems among Malay elderly residing in a rural community: A cross-sectional study," *PLoS ONE*, vol. 11, no. 6, Jun. 2016, Art. no. e0156937.

[2] WHO. (2022). *Mental Disorders*. Accessed: Jun. 2022. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/autism-spectrum-disorder

[3] ABS. *National Study of Mental Health and Wellbeing, 2020-21*. Accessed: Mar. 9, 2023. [Online]. Available: https://www.abs.gov.au/statistics/health/mental-health/national-study-mental-health-and-2022

[4] IHME. (2023). *Mental Illness*. Accessed: Mar. 2023. [Online]. Available: https://www.nimh.nih.gov/health/statistics/mental-illness

[5] M. H. A. Banna, A. Sayeed, S. Kundu, E. Christopher, M. T. Hasan, M. R. Begum, T. Kormoker, S. T. I. Dola, M. M. Hassan, S. Chowdhury, and M. S. I. Khan, "The impact of the COVID-19 pandemic on the mental health of the adult population in Bangladesh: A nationwide cross-sectional study," *Int. J. Environ. Health Res.*, vol. 32, no. 4, pp. 850–861, Apr. 2022.

[6] M. T. Hasan, T. Anwar, E. Christopher, S. Hossain, M. M. Hossain, K. N. Koly, K. M. Saif-Ur-Rahman, H. U. Ahmed, N. Arman, and S. W. Hossain, "The current state of mental healthcare in Bangladesh: Part 1—An updated country profile," *BJPsych Int.*, vol. 18, no. 4, pp. 78–82, Nov. 2021.

[7] Y. H. Wada, L. Rajwani, E. Anyam, E. Karikari, M. Njikizana, L. Srour, and G. M. Khalid, "Mental health in Nigeria: A neglected issue in public health," *Public Health Pract.*, vol. 2, Nov. 2021, Art. no. 100166.

[8] WHO. (2022). *Autism*. Accessed: Mar. 30, 2022. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/autism-spectrum-disorders

[9] H. C. McLane, A. L. Berkowitz, B. N. Patenaude, E. D. McKenzie, E. Wolper, S. Wahlster, G. Fink, and F. J. Mateen, "Availability, accessibility, and affordability of neurodiagnostic tests in 37 countries," *Neurology*, vol. 85, no. 18, pp. 1614–1622, Nov. 2015.

[10] C. Levin and D. Chisholm, "Cost-effectiveness and affordability of interventions, policies, and platforms for the prevention and treatment of mental, neurological, and substance use disorders," *Mental, Neurol., Substance Use Disorders, Disease Control Priorities*, vol. 4, no. 3, pp. 36–219, 2016.

[11] M. A. Sayem, M. S. R. Sarker, M. A. R. Ahad, and M. U. Ahmed, "Automatic epileptic seizures detection and EEG signals classification based on multi-domain feature extraction and multiscale entropy analysis," in *Signal Processing Techniques for Computational Health Informatics*. Springer, 2021, pp. 315–334.

[12] J. Gao, J. Hu, and W.-W. Tung, "Entropy measures for biological signal analyses," *Nonlinear Dyn.*, vol. 68, no. 3, pp. 431–444, May 2012.

[13] U. R. Acharya, S. V. Sree, P. C. A. Ang, R. Yanti, and J. S. Suri, "Application of non-linear and wavelet based features for the automated identification of epileptic EEG signals," *Int. J. Neural Syst.*, vol. 22, no. 2, Apr. 2012, Art. no. 1250002.

[14] U. R. Acharya, S. V. Sree, S. Chattopadhyay, and J. S. Suri, "Automated diagnosis of normal and alcoholic EEG signals," *Int. J. Neural Syst.*, vol. 22, no. 3, Jun. 2012, Art. no. 1250011.

[15] N. Kannathal, U. R. Acharya, C. M. Lim, and P. Sadasivan, "Characterization of EEG—A comparative study," *Comput. Methods Programs Biomed.*, vol. 80, no. 1, pp. 17–23, 2005.

[16] A. Ghaiyoumi. (2022). *Epilepsy*. Accessed: Apr. 25, 2022. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/epilepsy

[17] M. H. Kohrman, "What is epilepsy? Clinical perspectives in the diagnosis and treatment," *J. Clin. Neurophysiol.*, vol. 24, no. 2, pp. 87–95, 2007.

[18] H. Lalkhen and R. Mash, "Multimorbidity in non-communicable diseases in south African primary healthcare," *South Afr. Med. J.*, vol. 105, no. 2, pp. 134–138, 2015.

[19] U. R. Acharya, H. Fujita, V. K. Sudarshan, S. Bhat, and J. E. W. Koh, "Application of entropies for automated diagnosis of epilepsy using EEG signals: A review," *Knowl.-Based Syst.*, vol. 88, pp. 85–96, Nov. 2015.

[20] P. Joon, A. Kumar, and M. Parle, "What is autism?" *Pharmacol. Rep.*, vol. 73, no. 5, pp. 1255–1264, 2021.

[21] L. Gassner, M. Geretsegger, and J. Mayer-Ferbas, "Effectiveness of music therapy for autism spectrum disorder, dementia, depression, insomnia and schizophrenia: Update of systematic reviews," *Eur. J. Public Health*, vol. 32, no. 1, pp. 27–34, Feb. 2022.

[22] C. Raza, R. Anjum, and N. U. A. Shakeel, "Parkinson's disease: Mechanisms, translational models and management strategies," *Life Sci.*, vol. 226, pp. 77–90, Jun. 2019.

[23] A. Shkodina, T. Iengalychev, K. Tarianyk, D. Boiko, N. Lytvynenko, and A. Skrypnikov, "Relationship between sleep disorders and neuropsychiatric symptoms in Parkinson's disease: A narrative review," *Acta Facultatis Medicae Naissensis*, vol. 39, no. 3, pp. 259–274, 2022.

[24] C. Fang, L. Lv, S. Mao, H. Dong, and B. Liu, "Cognition deficits in Parkinson's disease: Mechanisms and treatment," *Parkinson's Disease*, vol. 2020, pp. 1–11, Mar. 2020.

[25] J. C. Greenland, C. H. Williams-Gray, and R. A. Barker, "The clinical heterogeneity of Parkinson's disease and its therapeutic implications," *Eur. J. Neurosci.*, vol. 49, no. 3, pp. 328–338, Feb. 2019.

[26] WHO. (2022). *Autism*. Accessed: Mar. 30, 2022. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/autism-spectrum-disorders

[27] R. Shah, S. Grover, and A. Avasthi, "Clinical practice guidelines for the assessment and management of attention-deficit/hyperactivity disorder," *Indian J. Psychiatry*, vol. 61, no. 8, p. 176, 2019.

[28] S. Weibel, O. Menard, A. Ionita, M. Boumendjel, C. Cabelguen, C. Kraemer, J.-A. Micoulaud-Franchi, S. Bioulac, N. Perroud, A. Sauvaget, L. Carton, M. Gachet, and R. Lopez, "Practical considerations for the evaluation and management of attention deficit hyperactivity disorder (ADHD) in adults," *L'Encephale*, vol. 46, no. 1, pp. 30–40, 2020.

[29] M. L. Zimmerman, "Attention-deficit hyperactivity disorders," *Nursing Clinics*, vol. 38, no. 1, pp. 55–66, 2003.

[30] R. Kieling and L. A. Rohde, "ADHD in children and adults: Diagnosis and prognosis," in *Behavioral Neuroscience of Attention Deficit Hyperactivity Disorder and Its Treatment*. Springer, 2012, pp. 1–16.

[31] L. Matheson, P. Asherson, I. C. K. Wong, P. Hodgkins, J. Setyawan, R. Sasane, and S. Clifford, "Adult ADHD patient experiences of impairment, service provision and clinical management in England: A qualitative study," *BMC Health Services Res.*, vol. 13, no. 1, pp. 1–13, Dec. 2013.

[32] M. Wolraich, L. Brown, R. Brown, G. DuPaul, M. Earls, H. Feldman, T. Ganiats, B. Kaplanek, B. Meyer, J. Perrin, K. Pierce, M. Reiff, M. T. Stein, and S. Visser, "ADHD: Clinical practice guideline for the diagnosis, evaluation, and treatment of attention-deficit/hyperactivity disorder in children and adolescents," *Pediatrics*, vol. 128, pp. SI1–SI21, Oct. 2011.

[33] P. Stępnicki, M. Kondej, and A. A. Kaczor, "Current concepts and treatments of schizophrenia," *Molecules*, vol. 23, no. 8, p. 2087, Aug. 2018.

[34] T. M. Laursen, M. Nordentoft, and P. B. Mortensen, "Excess early mortality in schizophrenia," *Annu. Rev. Clin. Psychol.*, vol. 10, no. 1, pp. 425–448, Mar. 2014.

[35] F. Mirakhori, M. Moafi, M. Milanifard, and H. Tahernia, "Diagnosis and treatment methods in Alzheimer's patients based on modern techniques: The orginal article," *J. Pharmaceutical Negative Results*, vol. 13, no. 1, pp. 1889–1907, 2022.

[36] M. G. Borda, H. Soennesyn, C. J. Steves, A. O. Vik-Mo, M. U. Pérez-Zepeda, and D. Aarsland, "Frailty in older adults with mild dementia: Dementia with Lewy bodies and Alzheimer's disease," *Dementia Geriatric Cognit. Disorders Extra*, vol. 9, no. 1, pp. 176–183, Apr. 2019.

[37] A. T. Isik, "Late onset Alzheimer's disease in older people," *Clin. Interventions Aging*, pp. 307–311, 2010.

[38] APA. (2023). *What is Depression?* [Online]. Available: https://www.psychiatry.org/patients-families/depression/what-is-depression

[39] C. D. Mathers and D. Loncar, "Projections of global mortality and burden of disease from 2002 to 2030," *PLoS Med.*, vol. 3, no. 11, p. e442, Nov. 2006.

[40] M. A. Schuckit, "Alcohol-use disorders," *Lancet*, vol. 373, no. 9662, pp. 492–501, 2009.

[41] N. Gökşen and S. Arıca, "A simple approach to detect alcoholics using electroencephalographic signals," in *Proc. Joint Conf. Eur. Med. Biol. Eng. Conf. (EMBEC) Nordic-Baltic Conf. Biomed. Eng. Med. Phys. (NBC)*, Tampere, Finland. Singapore: Springer, 2018, pp. 1101–1104.

[42] L. Jiajie, K. Narasimhan, V. Elamaran, N. Arunkumar, M. Solarte, and G. Ramirez-Gonzalez, "Clinical decision support system for alcoholism detection using the analysis of EEG signals," *IEEE Access*, vol. 6, pp. 61457–61461, 2018.

[43] T. P. Shri and N. Sriraam, "Spectral entropy feature subset selection using SEPCOR to detect alcoholic impact on gamma sub band visual event related potentials of multichannel electroencephalograms (EEG)," *Appl. Soft Comput.*, vol. 46, pp. 441–451, Sep. 2016.

[44] S. Taran and V. Bajaj, "Rhythm-based identification of alcohol EEG signals," *IET Sci., Meas. Technol.*, vol. 12, no. 3, pp. 343–349, May 2018.

[45] J. M. Morales, F. P. Bermejo, J. Benito-León, J. Rivera-Navarro, R. Trincado, R. S. Gabriel, and S. Vega, "Methods and demographic findings of the baseline survey of the NEDICES cohort: A door-to-door survey of neurological disorders in three communities from Central Spain," *Public Health*, vol. 118, no. 6, pp. 426–433, Sep. 2004.

[46] M. Placencia, J. W. A. S. Sander, S. D. Shorvon, R. H. Ellison, and S. M. Cascante, "Validation of a screening questionnaire for the detection of epileptic seizures in epidemiological studies," *Brain*, vol. 115, no. 3, pp. 783–794, 1992.

[47] N. Dahodwala, A. Siderowf, M. Baumgarten, A. Abrams, and J. Karlawish, "Screening questionnaires for parkinsonism: A systematic review," *Parkinsonism Rel. Disorders*, vol. 18, no. 3, pp. 216–224, Mar. 2012.

[48] A. J. Hughes, S. E. Daniel, Y. Ben-Shlomo, and A. J. Lees, "The accuracy of diagnosis of parkinsonian syndromes in a specialist movement disorder service," *Brain*, vol. 125, no. 4, pp. 861–870, Apr. 2002.

[49] S. M. Jungmann, T. Klan, S. Kuhn, and F. Jungmann, "Accuracy of a chatbot (Ada) in the diagnosis of mental disorders: Comparative case study with lay and expert users," *JMIR Formative Res.*, vol. 3, no. 4, Oct. 2019, Art. no. e13863.

[50] J. Ansado, C. Chasen, S. Bouchard, and G. Northoff, "How brain imaging provides predictive biomarkers for therapeutic success in the context of virtual reality cognitive training," *Neurosci. Biobehavioral Rev.*, vol. 120, pp. 583–594, Jan. 2021.

[51] K. D. Davis, H. Flor, H. T. Greely, G. D. Iannetti, S. Mackey, M. Ploner, A. Pustilnik, I. Tracey, R.-D. Treede, and T. D. Wager, "Brain imaging tests for chronic pain: Medical, legal and ethical issues and recommendations," *Nature Rev. Neurol.*, vol. 13, no. 10, pp. 624–638, Oct. 2017.

[52] S. Siuly and Y. Zhang, "Medical big data: Neurological diseases diagnosis through medical data analysis," *Data Sci. Eng.*, vol. 1, no. 2, pp. 54–64, Jun. 2016.

[53] A. A. Lima, M. F. Mridha, S. C. Das, M. M. Kabir, M. R. Islam, and Y. Watanobe, "A comprehensive survey on the detection, classification, and challenges of neurological disorders," *Biology*, vol. 11, no. 3, p. 469, Mar. 2022.

[54] D. Cohen, "Magnetoencephalography: Detection of the brain's electrical activity with a superconducting magnetometer," *Science*, vol. 175, no. 4022, pp. 664–666, Feb. 1972.

[55] A. Gonzalez-Montoro, J. Barbera, D. Sanchez, A. Mondejar, M. Freire, K. Diaz, A. Lucero, S. Jimenez-Serrano, J. Alamo, C. Morera-Ballester, J. Barrio, N. Cucarella, V. Ilisie, L. Moliner, C. Valladares, A. J. Gonzalez, J. Prior, and J. M. Benlloch, "A new brain dedicated PET scanner with 4D detector information," *Bio-Algorithms Med-Syst.*, vol. 18, no. 1, pp. 107–119, Dec. 2022.

[56] G. P. Tejay and Z. A. Mohammed, "Examining the low-resolution electromagnetic tomography technique for EEG brain mapping: Towards methodological advancement for IS research," *ACM SIGMIS Database, DATABASE Adv. Inf. Syst.*, vol. 54, no. 1, pp. 66–81, Feb. 2023.

[57] R. P. Turner, "Clinical application of combined EEG-qEEG functional neuroimaging in the practice of pediatric neuroscience: A personal perspective," *Clin. EEG Neurosci.*, vol. 52, no. 2, pp. 126–135, Apr. 2021.

[58] W. Bomela, S. Wang, C.-A. Chou, and J.-S. Li, "Real-time inference and detection of disruptive EEG networks for epileptic seizures," *Sci. Rep.*, vol. 10, no. 1, p. 8653, May 2020.

[59] K. AlSharabi, Y. B. Salamah, A. M. Abdurraqeeb, M. Aljalal, and F. A. Alturki, "EEG signal processing for Alzheimer's disorders using discrete wavelet transform and machine learning approaches," *IEEE Access*, vol. 10, pp. 89781–89797, 2022.

[60] A. U. Ibrahim, A. G. Kibarer, and F. Al-Turjman, "Computer-aided detection of tuberculosis from microbiological and radiographic images," *Data Intell.*, pp. 1–26, Feb. 2023, doi: 10.1162/dint_a_00198.

[61] R. Ranjan, R. Partl, R. Erhart, N. Kurup, and H. Schnidar, "The mathematics of erythema: Development of machine learning models for artificial intelligence assisted measurement and severity scoring of radiation induced dermatitis," *Comput. Biol. Med.*, vol. 139, Dec. 2021, Art. no. 104952.

[62] D. Cuesta–Frau, P. Miró–Martínez, J. J. Núñez, S. Oltra–Crespo, and A. M. Picó, "Noisy EEG signals classification based on entropy metrics. Performance assessment using first and second generation statistics," *Comput. Biol. Med.*, vol. 87, pp. 141–151, Aug. 2017.

[63] A. Delgado-Bonal and A. Marshak, "Approximate entropy and sample entropy: A comprehensive tutorial," *Entropy*, vol. 21, no. 6, p. 541, May 2019.

[64] F. Alù, F. Miraglia, A. Orticoni, E. Judica, M. Cotelli, P. M. Rossini, and F. Vecchio, "Approximate entropy of brain network in the study of hemispheric differences," *Entropy*, vol. 22, no. 11, p. 1220, Oct. 2020.

[65] O. K. Fasil and R. Rajesh, "Epileptic seizure classification using shifting sample difference of EEG signals," *J. Ambient Intell. Humanized Comput.*, pp. 1–14, Feb. 2022, doi: 10.1007/s12652-022-03737-9.

[66] O. Faust, P. C. A. Ang, S. D. Puthankattil, and P. K. Joseph, "Depression diagnosis support system based on EEG signal entropies," *J. Mech. Med. Biol.*, vol. 14, no. 3, Jun. 2014, Art. no. 1450035.

[67] H. Najafzadeh, M. Esmaeili, S. Farhang, Y. Sarbaz, and S. H. Rasta, "Automatic classification of schizophrenia patients using resting-state EEG signals," *Phys. Eng. Sci. Med.*, vol. 44, no. 3, pp. 855–870, Sep. 2021.

[68] J. S. Richman and J. R. Moorman, "Physiological time-series analysis using approximate entropy and sample entropy," *Amer. J. Physiol.-Heart Circulatory Physiol.*, vol. 278, no. 6, pp. H2039–H2049, Jun. 2000.

[69] C. E. Shannon, "A mathematical theory of communication," *ACM SIGMOBILE Mobile Comput. Commun. Rev.*, vol. 5, no. 1, pp. 3–55, 2001.

[70] C. Tsallis, "Possible generalization of Boltzmann-Gibbs statistics," *J. Stat. Phys.*, vol. 52, nos. 1–2, pp. 479–487, Jul. 1988.

[71] D. Wu, H. Jia, L. Abualigah, Z. Xing, R. Zheng, H. Wang, and M. Altalhi, "Enhance teaching-learning-based optimization for Tsallis-entropy-based feature selection classification approach," *Processes*, vol. 10, no. 2, p. 360, Feb. 2022.

[72] X. Gao, F. Liu, L. Pan, Y. Deng, and S. Tsai, "Uncertainty measure based on Tsallis entropy in evidence theory," *Int. J. Intell. Syst.*, vol. 34, no. 11, pp. 3105–3120, Nov. 2019.

[73] A. Rényi, "On measures of entropy and information," in *Proc. 4th Berkeley Symp. Math. Statist. Probab., Contrib. Theory Statist.*, vol. 4, Berkeley, CA, USA: Univ. of California Press, 1961, pp. 547–562.

[74] F. Safara and A. R. A. Ramaiah, "RenyiBS: Renyi entropy basis selection from wavelet packet decomposition tree for phonocardiogram classification," *J. Supercomput.*, vol. 77, no. 4, pp. 3710–3726, Apr. 2021.

[75] L. Xu, L. Bai, X. Jiang, M. Tan, D. Zhang, and B. Luo, "Deep Rényi entropy graph kernel," *Pattern Recognit.*, vol. 111, Mar. 2021, Art. no. 107668.

[76] A. Swami, J. M. Mendel, and C. L. Nikias, "Higher-order spectral analysis toolbox," Version 2, Mathworks, Natick, MA, USA, Tech. Rep., 1998, pp. 22–26, vol. 3.

[77] A. Ekhlasi, A. M. Nasrabadi, and M. Mohammadi, "Classification of the children with ADHD and healthy children based on the directed phase transfer entropy of EEG signals," *Frontiers Biomed. Technol.*, vol. 8, no. 2, pp. 115–122, Jun. 2021.

[78] J. Han, F. Dong, and Y. Y. Xu, "Entropy feature extraction on flow pattern of gas/liquid two-phase flow based on cross-section measurement," *J. Phys., Conf. Ser.*, vol. 147, Feb. 2009, Art. no. 012041.

[79] C. M. Stein, "Estimation of the mean of a multivariate normal distribution," *Ann. Statist.*, vol. 9, no. 6, pp. 1135–1151, Nov. 1981.

[80] R. C. Joy, S. T. George, A. A. Rajan, and M. S. P. Subathra, "Detection of ADHD from EEG signals using different entropy measures and ANN," *Clin. EEG Neurosci.*, vol. 53, no. 1, pp. 12–23, Jan. 2022.

[81] J. P. Zbilut, N. Thomasson, and C. L. Webber, "Recurrence quantification analysis as a tool for nonlinear exploration of nonstationary cardiac signals," *Med. Eng. Phys.*, vol. 24, no. 1, pp. 53–60, Jan. 2002.

[82] C. Bandt and B. Pompe, "Permutation entropy: A natural complexity measure for time series," *Phys. Rev. Lett.*, vol. 88, no. 17, Apr. 2002, Art. no. 174102.

[83] A. N. Kolmogorov, "A new metric invariant of transitive dynamical systems and automorphisms of Lebesgue spaces," *Trudy Matematicheskogo Instituta imeni VA Steklova* (Mathematics and Its Applications), vol. 27, pp. 94–98, 1985.

[84] M. Costa, A. L. Goldberger, and C.-K. Peng, "Multiscale entropy analysis of complex physiologic time series," *Phys. Rev. Lett.*, vol. 89, no. 6, Jul. 2002, Art. no. 068102.

[85] S.-D. Wu, C.-W. Wu, K.-Y. Lee, and S.-G. Lin, "Modified multiscale entropy for short-term time series analysis," *Phys. A, Stat. Mech. Appl.*, vol. 392, no. 23, pp. 5865–5873, Dec. 2013.

[86] B. Kosko, "Fuzzy entropy and conditioning," *Inf. Sci.*, vol. 40, no. 2, pp. 165–174, Dec. 1986.

[87] L. A. Zadeh, "Fuzzy sets," *Inf. Control*, vol. 8, no. 3, pp. 338–353, Jun. 1965.

[88] W. Chen, Z. Wang, H. Xie, and W. Yu, "Characterization of surface EMG signal based on fuzzy entropy," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 15, no. 2, pp. 266–272, Jun. 2007.

[89] A. Anuragi, D. S. Sisodia, and R. B. Pachori, "Automated FBSE-EWT based learning framework for detection of epileptic seizures using time-segmented EEG signals," *Comput. Biol. Med.*, vol. 136, Sep. 2021, Art. no. 104708.

[90] S. Nobukawa, T. Yamanishi, S. Kasakawa, H. Nishimura, M. Kikuchi, and T. Takahashi, "Classification methods based on complexity and synchronization of electroencephalography signals in Alzheimer's disease," *Frontiers Psychiatry*, vol. 11, p. 255, Apr. 2020.

[91] D. Bakheet and K. Maharatna, "Linear and nonlinear analysis of intrinsic mode function after facial stimuli presentation in children with autism spectrum disorder," *Comput. Biol. Med.*, vol. 133, Jun. 2021, Art. no. 104376.

[92] M. Rezaeezadeh, S. Shamekhi, and M. Shamsi, "Attention deficit hyperactivity disorder diagnosis using non-linear univariate and multivariate EEG measurements: A preliminary study," *Phys. Eng. Sci. Med.*, vol. 43, no. 2, pp. 577–592, Jun. 2020.

[93] M. Aljalal, S. A. Aldosari, K. AlSharabi, A. M. Abdurraqeeb, and F. A. Alturki, "Parkinson's disease detection from resting-state EEG signals using common spatial pattern, entropy, and machine learning techniques," *Diagnostics*, vol. 12, no. 5, p. 1033, Apr. 2022.

[94] P. T. Krishnan, A. N. J. Raj, P. Balasubramanian, and Y. Chen, "Schizophrenia detection using multivariate empirical mode decomposition and entropy measures from multichannel EEG signal," *Biocybernetics Biomed. Eng.*, vol. 40, no. 3, pp. 1124–1139, Jul. 2020.

[95] S. Mahato, N. Goyal, D. Ram, and S. Paul, "Detection of depression and scaling of severity using six channel EEG data," *J. Med. Syst.*, vol. 44, no. 7, pp. 1–12, Jul. 2020.

[96] G. Zhu, Y. Li, P. Wen, and S. Wang, "Analysis of alcoholic EEG signals based on horizontal visibility graph entropy," *Brain Informat.*, vol. 1, nos. 1–4, pp. 19–25, Dec. 2014.

[97] S. Patidar and T. Panigrahi, "Detection of epileptic seizure using Kraskov entropy applied on tunable-Q wavelet transform of EEG signals," *Biomed. Signal Process. Control*, vol. 34, pp. 74–80, Apr. 2017.

[98] M. Sharma, A. Dhere, R. B. Pachori, and U. R. Acharya, "An automatic detection of focal EEG signals using new class of time–frequency localized orthogonal wavelet filter banks," *Knowl.-Based Syst.*, vol. 118, pp. 217–227, Feb. 2017.

[99] Y. You, W. Chen, M. Li, T. Zhang, Y. Jiang, and X. Zheng, "Automatic focal and non-focal EEG detection using entropy-based features from flexible analytic wavelet transform," *Biomed. Signal Process. Control*, vol. 57, Mar. 2020, Art. no. 101761.

[100] H. Wang and D. Hu, "Comparison of SVM and LS-SVM for regression," in *Proc. Int. Conf. Neural Netw. Brain*, vol. 1, 2005, pp. 279–283.

[101] M. Syduzzaman, A. Rahman, S. Fujitani, A. Kashimori, T. Suzuki, Y. Ogawa, and N. Kondo, "Noninvasive quantification of EGG yolk ratio using vis-NIR spectroscopy and multivariate regression," *J. Jpn. Soc. Agricult. Machinery Food Engineers*, vol. 81, no. 3, pp. 168–176, 2019.

[102] N. Houmani, F. Vialatte, E. Gallego-Jutglà, G. Dreyfus, V.-H. Nguyen-Michel, J. Mariani, and K. Kinugawa, "Diagnosis of Alzheimer's disease with electroencephalography in a differential framework," *PLoS ONE*, vol. 13, no. 3, 2018, Art. no. e0193607.

[103] T.-T. Frie, N. Cristianini, and C. Campbell, "The Kernel-Adatron algorithm: A fast and simple learning procedure for support vector machines," in *Proc. 15th Int. Conf. Mach. Learn. (ICML)*, 1998, pp. 188–196.

[104] N. Renukadevi and P. Thangaraj, "Performance evaluation of SVM–RBF kernel for medical image classification," *Global J. Comput. Sci. Technol.*, vol. 13, pp. 15–19, May 2013.

[105] H. W. Loh, W. Hong, C. P. Ooi, S. Chakraborty, P. D. Barua, R. C. Deo, J. Soar, E. E. Palmer, and U. R. Acharya, "Application of deep learning models for automated identification of Parkinson's disease: A review (2011–2021)," *Sensors*, vol. 21, no. 21, p. 7034, Oct. 2021.

[106] C. Holingue, L. G. Kalb, K. E. Riehm, D. Bennett, A. Kapteyn, C. B. Veldhuis, R. M. Johnson, M. D. Fallin, F. Kreuter, E. A. Stuart, and J. Thrul, "Mental distress in the United States at the beginning of the COVID-19 pandemic," *Amer. J. Public Health*, vol. 110, no. 11, pp. 1628–1634, Nov. 2020.

[107] L. R. McKnight-Eily, C. A. Okoro, T. W. Strine, J. Verlenden, N. D. Hollis, R. Njai, E. W. Mitchell, A. Board, R. Puddy, and C. Thomas, "Racial and ethnic disparities in the prevalence of stress and worry, mental health conditions, and increased substance use among adults during the COVID-19 pandemic—-United Atates, April and May 2020," *Morbidity Mortality Weekly Rep.*, vol. 70, no. 5, pp. 162–166, Feb. 2021.

[108] B. C. Ekeh and U. E. Ekrikpo, "The knowledge, attitude, and perception towards epilepsy amongst medical students in Uyo, Southern Nigeria," *Adv. Med.*, vol. 2015, pp. 1–6, Mar. 2015.

[109] L. Strohm, C. Hehakaya, E. R. Ranschaert, W. P. C. Boon, and E. H. M. Moors, "Implementation of artificial intelligence (AI) applications in radiology: Hindering and facilitating factors," *Eur. Radiol.*, vol. 30, no. 10, pp. 5525–5532, Oct. 2020.

[110] D. P. dos Santos, D. Giese, S. Brodehl, S. H. Chon, W. Staab, R. Kleinert, D. Maintz, and B. Baeßler, "Medical students' attitude towards artificial intelligence: A multicentre survey," *Eur. Radiol.*, vol. 29, no. 4, pp. 1640–1646, Apr. 2019.

[111] G. Stiglic, P. Kocbek, N. Fijacko, M. Zitnik, K. Verbert, and L. Cilar, "Interpretability of machine learning-based prediction models in healthcare," *WIREs Data Mining Knowl. Discovery*, vol. 10, no. 5, p. e1379, 2020.

[112] J. Petch, S. Di, and W. Nelson, "Opening the black box: The promise and limitations of explainable machine learning in cardiology," *Can. J. Cardiol.*, vol. 38, no. 2, pp. 204–213, Feb. 2022.

[113] W. Samek and K.-R. Müller, "Towards explainable artificial intelligence," in *Explainable AI: Interpreting, Explaining and Visualizing Deep Learning*. Springer, 2019, pp. 5–22.

[114] D. Lee and S. N. Yoon, "Application of artificial intelligence-based technologies in the healthcare industry: Opportunities and challenges," *Int. J. Environ. Res. Public Health*, vol. 18, no. 1, p. 271, Jan. 2021.

[115] B. Babic, S. Gerke, T. Evgeniou, and I. G. Cohen, "Beware explanations from AI in health care," *Science*, vol. 373, no. 6552, pp. 284–286, Jul. 2021.

[116] M. A. Ahmad, C. Eckert, and A. Teredesai, "Interpretable machine learning in healthcare," in *Proc. ACM Int. Conf. Bioinf., Comput. Biol., Health Informat.*, 2018, pp. 559–560.

[117] G. Briganti and O. Le Moine, "Artificial intelligence in medicine: Today and tomorrow," *Frontiers Med.*, vol. 7, p. 27, Feb. 2020.

[118] M. Brunn, A. Diefenbacher, P. Courtet, and W. Genieys, "The future is knocking: How artificial intelligence will fundamentally change psychiatry," *Academic Psychiatry*, vol. 44, no. 4, pp. 461–466, Aug. 2020.

[119] D. Zhang and D. Shen, "Multi-modal multi-task learning for joint prediction of multiple regression and classification variables in Alzheimer's disease," *NeuroImage*, vol. 59, no. 2, pp. 895–907, Jan. 2012.

[120] J. Li and Q. Wang, "Multi-modal bioelectrical signal fusion analysis based on different acquisition devices and scene settings: Overview, challenges, and novel orientation," *Inf. Fusion*, vol. 79, pp. 229–247, Mar. 2022.

[121] N. Koutsouleris, T. U. Hauser, V. Skvortsova, and M. De Choudhury, "From promise to practice: Towards the realisation of AI-informed mental health care," *Lancet Digit. Health*, vol. 4, no. 11, pp. e829–e840, Nov. 2022.

[122] M. X. Henderson, M. Sengupta, J. Q. Trojanowski, and V. M. Y. Lee, "Alzheimer's disease tau is a prominent pathology in LRRK2 Parkinson's disease," *Acta Neuropathologica Commun.*, vol. 7, no. 1, pp. 1–16, Dec. 2019.

[123] K. S. Ma, H. Hasturk, I. Carreras, A. Dedeoglu, J. J. Veeravalli, J. Y. Huang, A. Kantarci, and J. C. Wei, "Dementia and the risk of periodontitis: A population-based cohort study," *J. Dental Res.*, vol. 101, no. 3, pp. 270–277, Mar. 2022.

[124] J. Drogt, M. Milota, S. Vos, A. Bredenoord, and K. Jongsma, "Integrating artificial intelligence in pathology: A qualitative interview study of users' experiences and expectations," *Mod. Pathol.*, vol. 35, no. 11, pp. 1540–1550, Nov. 2022.

[125] A. V. Perez-Sanchez, C. A. Perez-Ramirez, M. Valtierra-Rodriguez, A. Dominguez-Gonzalez, and J. P. Amezquita-Sanchez, "Wavelet transform-statistical time features-based methodology for epileptic seizure prediction using electrocardiogram signals," *Mathematics*, vol. 8, no. 12, p. 2125, Nov. 2020.

[126] B. Seifi, M. Barfi, and M. Esmaeilpour, "ECG-based prediction of epileptic seizures using machine learning methods," in *Proc. 9th Iranian Joint Congr. Fuzzy Intell. Syst. (CFIS)*, Mar. 2022, pp. 1–7.

[127] J. E. W. Koh, C. P. Ooi, N. S. Lim-Ashworth, J. Vicnesh, H. T. Tor, O. S. Lih, R.-S. Tan, U. R. Acharya, and D. S. S. Fung, "Automated classification of attention deficit hyperactivity disorder and conduct disorder using entropy features with ECG signals," *Comput. Biol. Med.*, vol. 140, Jan. 2022, Art. no. 105120.

[128] Y. Ru, J. Li, H. Chen, and J. Li, "Epilepsy detection based on variational mode decomposition and improved sample entropy," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–11, Jan. 2022.

[129] G. Jaffino, M. Sundaram, and J. Prabin Jose, "Weighted 1D-local binary pattern features and Taylor-Henry gas solubility optimization based deep maxout network for discovering epileptic seizure using EEG," *Digit. Signal Process.*, vol. 122, Apr. 2022, Art. no. 103349.

[130] Sukriti, M. Chakraborty, and D. Mitra, "Automated detection of epileptic seizures using multiscale and refined composite multiscale dispersion entropy," *Chaos, Solitons Fractals*, vol. 146, May 2021, Art. no. 110939.

[131] X. Lu, J. Zhang, S. Huang, J. Lu, M. Ye, and M. Wang, "Detection and classification of epileptic EEG signals by the methods of nonlinear dynamics," *Chaos, Solitons Fractals*, vol. 151, Oct. 2021, Art. no. 111032.

[132] S. Deivasigamani, C. Senthilpari, and W. H. Yong, "Machine learning method based detection and diagnosis for epilepsy in EEG signal," *J. Ambient Intell. Humanized Comput.*, vol. 12, no. 3, pp. 4215–4221, Mar. 2021.

[133] I. Wijayanto, R. Hartanto, and H. A. Nugroho, "Multi-distance fluctuation based dispersion fractal for epileptic seizure detection in EEG signal," *Biomed. Signal Process. Control*, vol. 69, Aug. 2021, Art. no. 102938.

[134] E. Abdulhay, V. Elamaran, M. Chandrasekar, V. Balaji, and K. Narasimhan, "Automated diagnosis of epilepsy from EEG signals using ensemble learning approach," *Pattern Recognit. Lett.*, vol. 139, pp. 174–181, Nov. 2020.

[135] S. T. George, M. S. P. Subathra, N. J. Sairamya, L. Susmitha, and M. J. Premkumar, "Classification of epileptic EEG signals using PSO based artificial neural network and tunable-Q wavelet transform," *Biocybernetics Biomed. Eng.*, vol. 40, no. 2, pp. 709–728, Apr. 2020.

[136] P. L. Rocha, A. K. Barros, W. S. Silva, G. C. Sousa, P. Sousa, and A. M. da Silva, "Classification of the interictal state with hypsarrhythmia from Zika virus congenital syndrome and of the ictal state from epilepsy in childhood without hypsarrhythmia in EEGs using entropy measures," *Comput. Biol. Med.*, vol. 126, Nov. 2020, Art. no. 104014.

[137] Y. Jiang, W. Chen, and Y. You, "Scattering transform-based features for the automatic seizure detection," *Biocybernetics Biomed. Eng.*, vol. 40, no. 1, pp. 77–89, Jan. 2020.

[138] M. Li, W. Chen, and T. Zhang, "FuzzyEn-based features in FrFT-WPT domain for epileptic seizure detection," *Neural Comput. Appl.*, vol. 31, no. 12, pp. 9335–9348, Dec. 2019.

[139] K. Singh and J. Malhotra, "IoT and cloud computing based automatic epileptic seizure detection using HOS features based random forest classification," *J. Ambient Intell. Humanized Comput.*, pp. 1–16, Dec. 2019, doi: 10.1007/s12652-019-01613-7.

[140] S. Raghu, N. Sriraam, Y. Temel, S. V. Rao, A. S. Hegde, and P. L. Kubben, "Performance evaluation of DWT based sigmoid entropy in time and frequency domains for automated detection of epileptic seizures using SVM classifier," *Comput. Biol. Med.*, vol. 110, pp. 127–143, Jul. 2019.

[141] P. Li, C. Karmakar, J. Yearwood, S. Venkatesh, M. Palaniswami, and C. Liu, "Detection of epileptic seizure based on entropy analysis of short-term EEG," *PLoS ONE*, vol. 13, no. 3, Mar. 2018, Art. no. e0193691.

[142] H. Göksu, "EEG based epileptiform pattern recognition inside and outside the seizure states," *Biomed. Signal Process. Control*, vol. 43, pp. 204–215, May 2018.

[143] O. Kocadagli and R. Langari, "Classification of EEG signals for epileptic seizures using hybrid artificial neural networks based wavelet transforms and fuzzy relations," *Expert Syst. Appl.*, vol. 88, pp. 419–434, Dec. 2017.

[144] Z.-K. Gao, Q. Cai, Y.-X. Yang, N. Dong, and S.-S. Zhang, "Visibility graph from adaptive optimal kernel time-frequency representation for classification of epileptiform EEG," *Int. J. Neural Syst.*, vol. 27, no. 4, Jun. 2017, Art. no. 1750005.

[145] S. Sareen, S. K. Sood, and S. K. Gupta, "An automatic prediction of epileptic seizures using cloud computing and wireless sensor networks," *J. Med. Syst.*, vol. 40, no. 11, pp. 1–18, Nov. 2016.

[146] P. Swami, T. K. Gandhi, B. K. Panigrahi, M. Tripathi, and S. Anand, "A novel robust diagnostic model to detect seizures in electroencephalography," *Expert Syst. Appl.*, vol. 56, pp. 116–130, Sep. 2016.

[147] K. Zeng, J. Yan, Y. Wang, A. Sik, G. Ouyang, and X. Li, "Automatic detection of absence seizures with compressive sensing EEG," *Neurocomputing*, vol. 171, pp. 497–502, Jan. 2016.

[148] G. Zhu, Y. Li, and P. P. Wen, "Epileptic seizure detection in EEGs signals using a fast weighted horizontal visibility algorithm," *Comput. Methods Programs Biomed.*, vol. 115, no. 2, pp. 64–75, Jul. 2014.

[149] Y. Kumar, M. L. Dewal, and R. S. Anand, "Epileptic seizure detection using DWT based fuzzy approximate entropy and support vector machine," *Neurocomputing*, vol. 133, pp. 271–279, Jun. 2014.

[150] C.-P. Shen, S.-T. Liu, W.-Z. Zhou, F.-S. Lin, A. Y.-Y. Lam, H.-Y. Sung, W. Chen, J.-W. Lin, M.-J. Chiu, M.-K. Pan, J.-H. Kao, J.-M. Wu, and F. Lai, "A physiology-based seizure detection system for multichannel EEG," *PLoS ONE*, vol. 8, no. 6, Jun. 2013, Art. no. e65862.

[151] Y. Song and J. Zhang, "Automatic recognition of epileptic EEG patterns via extreme learning machine and multiresolution feature extraction," *Expert Syst. Appl.*, vol. 40, no. 14, pp. 5477–5489, Oct. 2013.

[152] R. J. Martis, U. R. Acharya, J. H. Tan, A. Petznick, R. Yanti, C. K. Chua, E. Y. K. Ng, and L. Tong, "Application of empirical mode decomposition (EMD) for automated detection of epilepsy using EEG signals," *Int. J. Neural Syst.*, vol. 22, no. 6, Dec. 2012, Art. no. 1250027.

[153] C. Pappalettera, F. Miraglia, M. Cotelli, P. M. Rossini, and F. Vecchio, "Analysis of complexity in the EEG activity of Parkinson's disease patients by means of approximate entropy," *GeroScience*, vol. 44, no. 3, pp. 1599–1607, Jun. 2022.

[154] M. Murugappan, W. Alshuaib, A. K. Bourisly, S. K. Khare, S. Sruthi, and V. Bajaj, "Tunable Q wavelet transform based emotion classification in Parkinson's disease using electroencephalography," *PLoS ONE*, vol. 15, no. 11, Nov. 2020, Art. no. e0242014.

[155] G. Liu, Y. Zhang, Z. Hu, X. Du, W. Wu, C. Xu, X. Wang, and S. Li, "Complexity analysis of electroencephalogram dynamics in patients with Parkinson's disease," *Parkinson's Disease*, vol. 2017, pp. 1–9, Feb. 2017.

[156] E. Abdulhay, M. Alafeef, H. Hadoush, and N. Arunkumar, "A 64-channel scheme for autism detection via scaled conjugate gradient-based neural network classification of electroencephalogram ripples' complexity," *Expert Syst.*, vol. 40, no. 4, p. e13000, May 2023.

[157] S. Zhang, D. Chen, Y. Tang, and L. Zhang, "Children ASD evaluation through joint analysis of EEG and eye-tracking recordings with graph convolution network," *Frontiers Hum. Neurosci.*, vol. 15, May 2021, Art. no. 651349.

[158] S. Ibrahim, R. Djemal, and A. Alsuwailem, "Electroencephalography (EEG) signal processing for epilepsy and autism spectrum disorder diagnosis," *Biocybern. Biomed. Eng.*, vol. 38, no. 1, pp. 16–26, 2018.

[159] V. Gupta, T. Priya, A. K. Yadav, R. B. Pachori, and U. R. Acharya, "Automated detection of focal EEG signals using features extracted from flexible analytic wavelet transform," *Pattern Recognit. Lett.*, vol. 94, pp. 180–188, Jul. 2017.

[160] R. Djemal, K. AlSharabi, S. Ibrahim, and A. Alsuwailem, "EEG-based computer aided diagnosis of autism spectrum disorder using wavelet, entropy, and ANN," *BioMed Res. Int.*, vol. 2017, pp. 1–9, 2017.

[161] W. J. Bosl, T. Loddenkemper, and C. A. Nelson, "Nonlinear EEG biomarker profiles for autism and absence epilepsy," *Neuropsychiatric Electrophysiology*, vol. 3, no. 1, pp. 1–22, Dec. 2017.

[162] Z. Song, B. Deng, J. Wang, and R. Wang, "Biomarkers for Alzheimer's disease defined by a novel brain functional network measure," *IEEE Trans. Biomed. Eng.*, vol. 66, no. 1, pp. 41–49, Jan. 2019.

[163] M. Buscema, F. Vernieri, G. Massini, F. Scrascia, M. Breda, P. M. Rossini, and E. Grossi, "An improved I-FAST system for the diagnosis of Alzheimer's disease from unprocessed electroencephalograms by using robust invariant features," *Artif. Intell. Med.*, vol. 64, no. 1, pp. 59–74, May 2015.

[164] Y. Cao, L. Cai, J. Wang, R. Wang, H. Yu, Y. Cao, and J. Liu, "Characterization of complexity in the electroencephalograph activity of Alzheimer's disease based on fuzzy entropy," *Chaos, Interdiscipl. J. Nonlinear Sci.*, vol. 25, no. 8, Aug. 2015, Art. no. 083116.

[165] N. Houmani, G. Dreyfus, and F. B. Vialatte, "Epoch-based entropy for early screening of Alzheimer's disease," *Int. J. Neural Syst.*, vol. 25, no. 8, Dec. 2015, Art. no. 1550032.

[166] R. Wang, J. Wang, S. Li, H. Yu, B. Deng, and X. Wei, "Multiple feature extraction and classification of electroencephalograph signal for Alzheimers' with spectrum and bispectrum," *Chaos, Interdiscipl. J. Nonlinear Sci.*, vol. 25, no. 1, Jan. 2015, Art. no. 013110.

[167] R. Yaghoobi, S. Azadi, and P. Keshavarzi, "Loss detection of recurrence rate in the EEG signals of children with ADHD," *J. Sci. Ind. Res.*, vol. 78, pp. 203–211, 2019.

[168] S. Khoshnoud, M. A. Nazari, and M. Shamsi, "Functional brain dynamic analysis of ADHD and control children using nonlinear dynamical features of EEG signals," *J. Integrative Neurosci.*, vol. 17, no. 1, pp. 17–30, Feb. 2018.

[169] B. Abibullaev and J. An, "Decision support algorithm for diagnosis of ADHD using electroencephalograms," *J. Med. Syst.*, vol. 36, no. 4, pp. 2675–2688, Aug. 2012.

[170] C. Jiang, Y. Li, Y. Tang, and C. Guan, "Enhancing EEG-based classification of depression patients using spatial information," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 566–575, 2021.

[171] Q. Shi, A. Liu, R. Chen, J. Shen, Q. Zhao, and B. Hu, "Depression detection using resting state three-channel EEG signal," 2020, *arXiv:2002.09175*.

[172] M. Čukić, M. Stokić, S. Simić, and D. Pokrajac, "The successful discrimination of depression from EEG could be attributed to proper feature extraction and not to a particular classification method," *Cognit. Neurodynamics*, vol. 14, no. 4, pp. 443–455, Aug. 2020.

[173] S. Mahato and S. Paul, "Detection of major depressive disorder using linear and non-linear features from EEG signals," *Microsyst. Technol.*, vol. 25, no. 3, pp. 1065–1076, Mar. 2019.

[174] H. Lai, J. Feng, Y. Wang, W. Deng, J. Zeng, T. Li, J. Zhang, and K. Liu, "Resting-state electroencephalogram classification of patients with schizophrenia or depression," *Sheng wu yi xue Gong Cheng xue za zhi=J. Biomed. Engineering=Shengwu Yixue Gongchengxue Zazhi*, vol. 36, no. 6, pp. 916–923, 2019.

[175] H. Cai, Y. Chen, J. Han, X. Zhang, and B. Hu, "Study on feature selection methods for depression detection using three-electrode EEG data," *Interdiscipl. Sci., Comput. Life Sci.*, vol. 10, no. 3, pp. 558–565, Sep. 2018.

[176] S. D. Puthankattil and P. K. Joseph, "Half-wave segment feature extraction of EEG signals of patients with depression and performance evaluation of neural network classifiers," *J. Mech. Med. Biol.*, vol. 17, no. 1, Feb. 2017, Art. no. 1750006.

[177] G. M. Bairy, U. C. Niranjan, and S. D. Puthankattil, "Automated classification of depression EEG signals using wavelet entropies and energies," *J. Mech. Med. Biol.*, vol. 16, no. 3, May 2016, Art. no. 1650035.

[178] S. D. Puthankattil and P. K. Joseph, "Classification of EEG signals in normal and depression conditions by ANN using RWE and signal entropy," *J. Mech. Med. Biol.*, vol. 12, no. 4, Sep. 2012, Art. no. 1240019.

[179] K. Masychev, C. Ciprian, M. Ravan, J. P. Reilly, and D. MacCrimmon, "Advanced signal processing methods for characterization of schizophrenia," *IEEE Trans. Biomed. Eng.*, vol. 68, no. 4, pp. 1123–1130, Apr. 2021.

[180] S. K. Prabhakar, H. Rajaguru, and S.-H. Kim, "Schizophrenia EEG signal classification based on swarm intelligence computing," *Comput. Intell. Neurosci.*, vol. 2020, pp. 1–14, Nov. 2020.

[181] M. Sabeti, R. Behroozi, and E. Moradi, "Analysing complexity, variability and spectral measures of schizophrenic EEG signal," *Int. J. Biomed. Eng. Technol.*, vol. 21, no. 2, pp. 109–127, 2016.

[182] G. M. Bairy, U. C. Niranjan, S. L. Oh, J. E. W. Koh, V. K. Sudarshan, J. H. Tan, Y. Hagiwara, and E. Y. K. Ng, "Alcoholic index using nonlinear features extracted from different frequency bands," *J. Mech. Med. Biol.*, vol. 17, no. 7, Nov. 2017, Art. no. 1740009.

[183] T. K. P. Shri and N. Sriraam, "Performance evaluation of classifiers for detection of alcoholics using electroencephalograms (EEG)," *J. Med. Imag. Health Informat.*, vol. 2, no. 3, pp. 289–295, Sep. 2012.

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