CHAPTER 7

Dementia diagnosis with EEG using machine learning

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Introduction

Dementia is a group of symptoms due to any chronic neuropsychiatric brain disorder, leading to impaired cognitive capability and memory loss (Scott & Barrett, 2007). The Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) defines significant cognitive impairment as a major neurocognitive disorder or dementia (American Psychiatric Association, 2013). It is also known as an age-related disorder. Its symptoms include impairment of brain functions, memory, thinking, orientation, comprehension, calculation, learning capacity, language, and judgment. Dementia patients do not lose consciousness, but they can become dependent on others because of neurological maladies and cognitive impairment. DSM-5 lists more than 12 etiological causes of dementia. Some of the most common types of dementia are Alzheimer's disease (AD), vascular dementia (VD), Lew body dementia, and Parkinson's disease (PD) (American Psychiatric Association, 2013). The major cause of dementia in Western countries is AD, and 60%–80% of dementia cases with AD occur in the United States (Bird, 2001) (see Table 1). AD is characterized by the presence of cortical amyloid plaques and neurofibrillary tangles in the brain (Hebert, Scherr, Bienias, Bennett, & Evans, 2003; Scott & Barrett, 2007). VD is caused by a disruption in blood supply to the brain, typically caused by stroke. It is the second most common cause of dementia worldwide. According to DSM-5 (American Psychiatric Association, 2013), AD and VD have the most complex symptomology as they have many similarities in diagnostic criteria and early symptoms. If dementia is caused by more than two neurodegenerative diseases, it is called as mixed dementia. The prevalence of frontotemporal lobar degeneration (FTLD), which is caused by frontal

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Table 1 The prevalence of dementia type.

Dementia type	Symptoms	Cause	Prevalence
Alzheimer's disease (AD)	A slow cognitive decline that involves memory loss, apathy, and depression	Cortical amyloid plaques and neurofibrillary tangles	50%–75%
Vascular dementia (VD)	Similar symptoms to AD, but with less memory impairment; decline in executive functioning with emotional variation; proceeds in a step-by-step progression	Cerebrovascular disease, single infarcts in critical regions, or more diffuse multiinfarct disease	20%–30%
Franto-temporal dementia	Behavioral variant, fluent and progressive nonfluent aphasia, mood changes, disinhibition, and personality changes	Damage in frontal and temporal cortex	5%–10%
Dementia with Lewy bodies	Labeled variation in cognitive abilities, hallucinations, parietal/frontal involvement, and parkinsonism	Cortical Lewy bodies (alpha synuclein)	<5%

and temporal lobe atrophy, is 5%–10% in developed countries worldwide (Ferri, Sousa, Albanese, Ribeiro, & Honyashiki, 2009). Some rare cases of dementia are diagnosed by a surgical situation such as hypercalcemia, subdural hematoma, normal pressure hydrocephalus (NPH), and deficiencies of thyroid hormone, vitamin B12, and folic acid (World Health Organization, 2006). Due to lack of awareness in rural India, sometimes dementia is cosidered as normal aging and not treated as medical issue (Shaji, Smitha, Lal, & Prince, 2003).

To diagnose dementia, clinicians need to assess the impairment in cognitive functions, memory, and independent daily living skills. Thus, mild cognitive impairment (MCI) can be an early sign of different neurological conditions that finally leads to memory deficit or dementia. Cognition plays a critical role in many neurodegenerative diseases. MCI is defined as a mild reduction in one or two cognitive abilities, such as remembering things and recalling skills, focusing, managing bills and money, communicating, perceptual and motor skills, and recognizing people. It is also known as mild neurocognitive disorder (American Psychiatric Association, 2013).

Prevalence of dementia worldwide

Demographic aging is a natural phenomenon and is increasing in developing and low-income countries. India's population is experiencing a sharp demographic shift at present. More than 90 million people are 65 years and older, as per the 2019 census in India, which is only 6.57% of the whole population. However, in the future there will be a definite increase in the elderly population.

Along with a sharp rise in demographic shift, fast-paced social restructuring following economic growth is occurring. This is a challenging situation in regard to meeting the needs of the elderly population. Demographic aging also brings with it the problem of dementia, cases of which double in number every 5 years. Thus, India will have massive numbers of elderly people with dementia in the future. There are 50 million dementia patients globally and this number is expected to increase to 152 million by 2050. One case of dementia is diagnosed every 3 s. The present cost of dementia treatment in the United States is $1 trillion and this cost will double by 2030 (Alzheimer's Disease International, 2019). These calculations are relatively 12%–13% more than those projected by the World Alzheimer Report 2009 (Ferri et al., 2009). This report projected 115.4 million in 2050 compared to 41.5 million in 2015. It also estimated that more than 50% of dementia patients would be from low- and middle-income countries. More than 90% of dementia patients receive at-home care (Prince, 2015). Around 42,000 elder investigated at eight sites of India by Alzheimer's and Related Disorders Society of India (ARDSI) and observed wide variations in estimation of dementia prevalence (Shaji et al., 2010). The diagnostic gap is widening due to the absence of a sensitive and specific diagnostic tool for dementia. Such a tool must not have dialectal, educational, and cultural barriers. Dementia studies are limited in India, but one report estimated that Delhi, Bihar, and Jharkhand will experience a 200% increase in dementia cases in 2026 compared to 2006 (Shaji et al., 2010). Worldwide reports show that around 36 million dementia patients do not receive proper diagnosis (Prince, Bryce, & Ferri, 2011). Early dementia diagnosis will allow patients to access information, resources, and support in advance. Early diagnosis will also enhance patient quality of life and treatment.

Electroencephalogram

An electroencephalogram (EEG) is an image of recorded scalp electrical activity generated by the brain. EEG measures voltage fluctuations occurring from ionic current flows within the neurons of the brain. The high temporal resolution of EEG can measure brain signals at a rate of less than 1 ms, which is an advantage over other techniques of measuring brain activity. EEG recording is entirely noninvasive and can be used on adults and children without any limitations. Modern EEG has high spatial resolution where up to 256 electrode sites can record at the same time. The brain signals are produced in all mental states (normal and abnormal). EEG can reflect all brain activity, so it is a potent tool for neurological and psychological diseases. EEG patterns are commonly sinusoidal signals. EEG ranges from 0.5 to 100 μV in amplitude and comprises frequency components of up to 300 Hz. Various frequencies of sine waves are obtained from a raw EEG signal using Fourier or wavelet transform. Every cognitive state of the brain generates frequencies; sometimes certain frequencies are more dominant. Brain waves are categorized into the following:

- Delta waves (δ) (range 0–4 Hz): These waves have the highest amplitude. They are emitted by adults in slow-wave sleep and occur naturally in babies and children.
- Theta waves (θ) (range 4–8 Hz): These waves are usually observed in growing children. Theta waves occur during both drowsiness and arousal states in adolescents and adults. Theta power is prominent during meditation. Profuse theta waves with age depict abnormal activity.
- Alpha waves (α) (range 8–12 Hz): These waves occur during relaxed states of mind and usually when a person's eyes are closed. They attenuate with eye-opening or mental exertion.
- Sensory motor response (12–13 Hz): This response generates from the brain's sensory-motor cortex. It is responsible for human body movements.
- Beta waves (β) (range 12–30 Hz): Beta activity attenuates during active movements. Beta waves usually occur during working, involved or concerned thought, and intense attention.
- Gamma waves (γ) (range >30 Hz): These waves occur during different cognitive and motor functions such as cross-modal sensory processing and short-term memory. Gamma waves decline with cognitive deterioration.

Cognitive testing and EEG

Cognition is the process whereby individuals acquire knowledge from the environment. Mental states, such as arousal, workload, and working memory, reflect central nervous system and automatic nervous system activity. Cognitive neuroscience has become crucial for establishing the scientific foundation and brain function principles associated with human performance. Dementia refers to cognitive decline, which is why the conventional method of detection was neuropsychological test batteries; however, these tests fail to diagnose dementia alone due to lack of cross validation with physiology. Many studies have proven that EEG recordings with cognitive tasks achieve better diagnostic results than resting-state EEG signals. The EEG signal of a dementia patient demonstrates the functional changes in the cerebral cortex. The symptoms of dementia develop slowly in the early stages and are often confused with impairments due to normal aging with etiologies. The symptoms become more obvious as dementia progresses, as shown in Fig. 1, and thus cognition and functional ability begin to decline. A major challenge is differentiating the early stages of dementia from normal age-related changes in memory and thinking. Determining the date of onset of dementia and estimating its occurrence rate is difficult due to its progressive nature. Usually, dementia onset occurs with MCI. Hence, the likelihood of identifying early stages of dementia and MCI is very low. Also, all types of dementia symptoms are similar, but their expression differs from patient to patient. This factor diminishes the possibility of differentiating dementia from other types of cognitive decline (Phillips, Pond, & Goode, 2011).

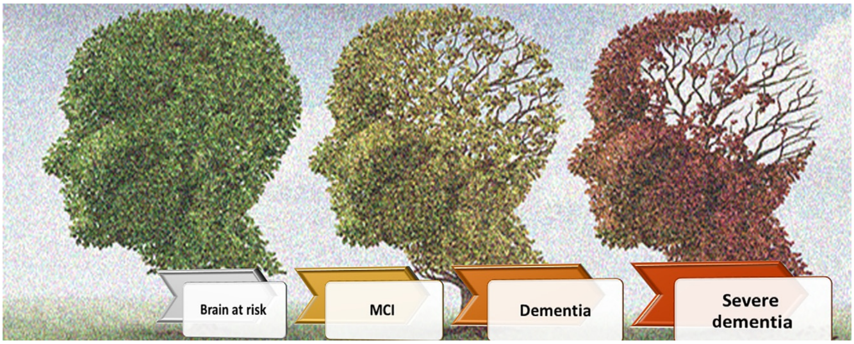

Fig. 1 Different stages of dementia.

One study of MCI patients found that coherence and power of EEG signal bands are greater in patients during a working memory task (Jiang, 2005). Previous studies have already explained age-related changes in EEG during cognitive tasks and showed significant differences between healthy young people and healthy older people (Widagdo, Pierson, & Helme, 1998). Similarly, EEG combined with a cognitive task can improve accuracy of detecting different types of dementia. Every type has different early signs of cognitive decline, as shown in Table 1. For example, memory impairment occurs first in AD, whereas decline in executive function occurs first in VD. Frontotemporal dementia shows a behavioral variant. Sometime patients also suffer from mixed-type dementia (Rossor, Fox, Mummery, Schott, & Warren, 2010). Much recent research has investigated the use of EEG to diagnose AD as well as other brain disorders. However, accuracy is still a challenge in diagnosing MCI, in which anatomical brain changes are minimal.

Moreover, it is not feasible to measure the cause of cognitive decline in MCI, which is confused with normal subjects. Even though dementia is possible with any neurodegenerative disease, everyone with MCI progresses to dementia. Some studies have tried to differentiate progressive from stable MCI (Missonnier et al., 2007). Therefore, a different kind of tool is necessary because every disease has different treatments, interventions, and cures. To design a proper tool for diagnosis, a combination of cognitive screening and EEG analysis with machine learning are required for specific disorders by considering all the challenged involved in the diagnosis as projected in Fig. 2. Cognitive screening tools are beneficial for the subject identification from the mass population in the beginning. This can save cost of further diagnosis (Sharma, Kolekar, & Chandra, 2015). Additionally, EEG analysis aids in exploring brain activity during a cognitive test, which is not feasible with imaging techniques. Lastly, ML techniques help to obtain the desired diagnostic accuracy.

Meanwhile, emerging technologies play an essential role in making neuropsychological tests more user-friendly and less time-consuming, such as those accessible via Android or iOS apps. These apps are cost-effective, transportable, and convenient for diagnosing large populations. Consequently, dementia diagnosis requires a fusion of cognitive tests, EEG signal processing, and ML, as shown in Fig. 2. EEG-based dementia diagnosis has improved over time. It is noninvasive, inexpensive, and portable. Recently, studies of EEG and ML techniques have shown good sensitivity and specificity in comparison to imaging studies in diagnosing AD, seizure, and

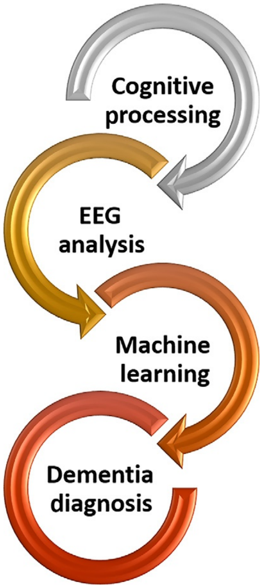

Fig. 2 EEG-based proposed model.

dementia (Bennys, Rondouin, Vergnes, & Touchon, 2001; Benvenuto, Jin, Casale, Lynch, & Granger, 2002; Jeong, 2004; Kolekar & Dash, 2015). Traditionally, EEG is acquired at a resting state for diagnosing diseases such as epilepsy, Creutzfeldt-Jakob disease, and other etiologies. EEG during cognitive processing is used for research purposes to investigate the physiology of the human brain more accurately. In the last few years, cognitive test performance and EEG information obtained during the test has proven to be a potential diagnostic tool for dementia (Durongbhan et al., 2019; Mcbride et al., 2014; Sharma et al., 2020, 2019). There are three important EEG parameters to consider when using this modality to diagnose dementia: slowing of EEG, reduction in complexity, perturbed synchronization (Dauwels, Vialatte, & Cichocki, 2010). Dementia diagnosis using EEG has four basic steps: (1) data acquisition, (2) signal preprocessing, (3) feature extraction, and (4) classification, as shown in Fig. 3.

Data acquisition

Traditionally, diagnostic EEG is done with the patient lying down with both eyes closed for a few minutes and then with both eyes open for a few minutes and later on photonic stimulus is given to the patients. The EEG pattern is analyzed by expert technicians and medical practitioners according to the

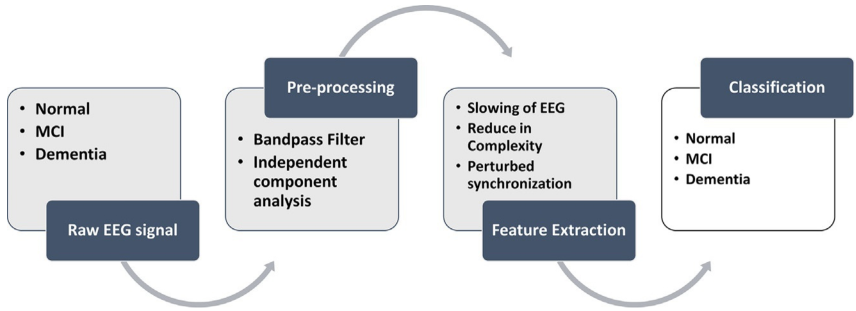

Fig. 3 EEG-based approach for classification of dementia.

patient's history and symptomatology. Severe dementia patients are hard to handle in a cognitive task, and they barely respond to any test question. Thus, the patient's EEG recording at resting state condition utilize as a reference to the milder stages of dementia. For early dementia diagnosis, cognitive task studies have analyzed EEG signal records along with patient performance on cognitive tasks (Sharma et al., 2019). Sometimes, event-related potentials (ERPs), such as visual and auditory stimuli potentials, are also recorded to investigate stimulus response in the brain.

Preprocessing of EEG signal

Preprocessing of the EEG signal is required because noise factors diminish the accuracy of the EEG record and most artifacts overlap with the frequencies of the signal. Physiological artifacts are due to muscle activities, pulse, and eye blinking. Nonphysiological artifacts are due to power line interference noise and sweat (Jung et al., 2000). Various signal preprocessing methods are used to eliminate the noise from a recorded EEG signal. Adaptive filtering and independent component analysis (ICA) are effective preprocessing methods (Kilicarslan, Grossman, & Contreras-Vidal, 2016; Roy & Shukla, 2015). The wavelet transform (WT) is an efficient denoising method to treat nonstationary EEG. A few recent studies have applied WT to remove visual artifacts and detect epileptic seizure (Krishnaveni, Jayaraman, Aravind, Hariharasudhan, & Ramadoss, 2006; Kumar & Kolekar, 2014; Zikov, Bibian, Dumont, Huzmezan, & Ries, 2002).

Feature extraction

EEG-based diagnosis of dementia can be broadly categorized into two categories of feature extraction: linear spectral analysis and nonlinear dynamics.

The linear and nonlinear methods of analysis measure the three essential parameters of dementia diagnosis: slowing of EEG, reduced complexity, and disturbed synchronization, as shown in Fig. 3. Table 2 shows the different features used in different studies.

Linear approach

EEG analysis in the frequency and time-frequency domains is considered a linear approach that involves Fourier and wavelet transform. The mother wavelet types utilized in EEG denoising are Daubechies, Coiflets, and Dyme. An early diagnostic method based on multiresolution wavelet analysis of ERP has been proposed. EEG signal is decomposed into coarse approximation by discrete wavelet transform (DWT) and a multiresolution analysis. In this diagnostic method, a neural network is trained to extract various features for diagnosis of dementia. Here, DWT was used to represent ERPs compactly (Polikar, Keinert, & Greer, 2001).

The linear relationship between electrodes in cases of dementia are studied by different types of feature such as EEG relative power, coherence, and Granger causality. Dementia slows down the EEG signals and causes a power increase in lower frequency bands (delta and theta bands) and a power decrease in higher frequency bands (alpha and beta bands), which is known as slowing of EEG. Nevertheless, when comparing AD patients with the healthy group, a power increase in the gamma band of EEG signals has been reported (Dauwels, Vialatte, & Cichocki, 2010; Jeong, 2004). A recent study (Rodriguez et al., 2014) proposed an EEG spectral analysis-based method for early diagnosis of AD. The research was carried out with three subject groups: probable AD, asymptomatic carrier, and healthy groups. Twenty-four artifact-free epochs of 2.56 ms were selected for the quantitative analysis, and the Fourier transform of each epoch was calculated. The broadband spectral parameters of mean frequency, relative power, and absolute power were calculated for delta, theta, alpha, and beta bands. Afterwards, 50 Hz notch filter is applied to remove electrical interference (Szava et al., 1994).

Spectral EEG analysis can quantify the severity of dementia and achieve a more reliable dementia diagnosis. Better features allow the classifier to identify signals more accurately. Spectral analysis also helps in differentiating between different types and causes of dementia. Neto, Allen, Aurlien, Nordby, and Eichele (2015) proposed a model that significantly differentiates AD and VD based on EEG features such as frequency amplitudes, the decay of amplitude from low to high frequencies, alpha frequency,

Table 2 Different cognitive tests for dementia and their techniques and features.

Study	Dataset	EEG/ERP	Technique and features
Sharma, Kolekar, and Jha (2020) with finger tapping test (FTT) and continuous performance test (CPT)	Dementia = 16; MCI/ED = 16; healthy = 15	13 min	Power spectral density (PSD), variance, fractal dimension(FD), and Tsallis entropy (TE) using iterative filtering decomposition
Li, Xiao, Li, Li, and Yang (2020) cognitive reappraisal task	MCI = 15; healthy = 15	5 min	Variance, RMS amplitude, Hjorth parameters, zero crossings, skewness and kurtosis, five EEG band Shannon entropy, singular value decomposition, entropy, Fisher information, and spectral entropy
Sharma, Kolekar, Jha, and Kumar (2019) with FTT and CPT	Dementia = 15; MCI = 16; control = 13	13 min	PSD, SE, spectral features, and FD using wavelet packet decomposition
A visual oddball task (Wang, Xu, Zhao, & Lou, 2019)	VD =15; control= 21	2.64 s (ERP)	Directed transfer function of power
Memory recall task ()	VD = 5; MCI = 15; normal = 15	60 s	Relative powers, permutation entropy, and FD using fuzzy neighborhood preserving analysis with QR decomposition
Auditory oddball paradigm (Staudinger & Polikar, 2011)	AD = 79; control = 82	30 min (ERP)	Higuchi FD, spectral entropy (SE), spectral centroid (SC), spectral roll-off (SR), and zero-crossing rate (ZCR)
Boston naming test (Reyes-Coronel et al., 2016)	Rapid cognitive decline (RCD) = 15; non-RCD = 53	NA	SE, TE, Granger causality (GC), auto MI, conditional GC, canonical correlation (CC), dynamic CC, FD, PSD, partial and phase coherence
Counting backwards with finger tapping (Mcbride et al., 2014)	Control = 15; early MCI = 16; early stage AD = 17	10 min	PSD, spectral features, entropy first derivative

and power. A decline in coherence is an important linear feature of the EEG signal that describes the spectral correlation between two EEG signals recorded at an electrode pair. Coherence C can be mathematically calculated by

$$C = |f_{xy}|^2/(f_{xx} \cdot f_{yy}) \tag{1}$$

where f_{xy} denotes a spectral estimation of a pair of electrodes recorded signals x and y for a given frequency band. Further, the mean phase coherence computed describes the phase synchronization between two signals, unlike mean square amplitude coherence (Che, Jung, Im, & Lee, 2007). Some recent research has introduced wavelet coherence, which is considered more sensitive to brainwave alterations during the cognitive process than traditional coherence (Vyšata, Vališ, Procházka, Rusina, & Pazdera, 2015).

Granger casualty is another linear measure used for extraction and the computation of directionality from EEG signals and is based on the bivariate autoregressive estimate of the EEG data. It includes partial directed coherence (PDC) and directed transfer function (DTF) extracted from multichannel data. DTF has an advantage over spectral coherence; it can determine the directionality in the coupling when the frequency spectra of the two brain regions have overlapping spectra (Sanei & Chambers, 2013). According to studies on Granger causality in cases of MCI, DTF significantly reduced in MCI and AD patients as did the direction of the information flow from parietal to frontal (Babiloni et al., 2009).

Nonlinear approach

An EEG signal has nonlinear behavior due to the brain's complex construction of synapses and neurons. The EEG signal presents the chaotic nature of the nervous system. Therefore, the nonlinear approach has the advantage to provide additional in-formation in comparison to the linear approach. Unlike the linear methods, nonlinear analysis methods measure the complexity and stability of the brain waves. Various nonlinear features such as entropy, fractal dimension (FD), Lyapunov exponent (LE), mutual information (MI), correlation dimension (CD), zero-crossing rate (ZCR), and weight permutation entropy (WPE) are used to detect MCI and dementia.

Initially, CD and LE are used as nonlinear features to detect the dynamical system's complexity (Grassberger & Procaccia, 2004; Wolf, Swift,Swinney, & Vastano, 1985). CD is the measure of FD, often referred to as dimensional complexity (Besthorn, Sattel, Geiger-Kabisch, Zerfass,

& Förstl, 1995). FD is a quotient providing a statistical degree of complexity. It measures the variation in pattern. There is a different type of FD, but few classical fractals, including CD, Kurts, and Higuchi dimensions (HD), are used in the case of AD and dementia diagnosis (Henderson, Ifeachor, Wimalaratna, Allen, & Hudson, 2000; Rodríguez-Bermúdez & García-Laencina, 2015; Sharma et al., 2020; Staudinger & Polikar, 2011). Some prior research has revealed that AD patients have fewer CD/FD values at parietal and temporal regions than healthy people do (Adeli, Ghosh-Dastidar, & Dadmehr, 2008; Das, Das, & Roy, 2002; Sanei & Chambers, 2013). However, a positive larger LE value signifies the chaotic system, while a negative LE shows fewer changes, and zero LE indicates no change (Adeli et al., 2008; Das et al., 2002; Sanei & Chambers, 2013). There are two well-known algorithms for LE used for EEG data: wolf's algorithm (Wolf et al., 1985), and Rosenstein's method (Rosenstein, Collins, & De Luca, 1993). These measures are limited to quantifying irregular behavior of brain patterns and are sensitive to parameters such as embedding dimension, time delay, and data length (Henderson et al., 2006). However, LE is related to the entropy of the chaotic or dynamic system. Entropy measures the uncertainty and greater uncertainty correlates to greater entropy and more chaotic nature of the brain. Entropy is defined as

$$x(n) = \int_{\min(x)}^{\max(x)} p_x \log(1/p_x)dx \tag{2}$$

where p_x is the probability density function of a signal $x(n)$. Entropy is very sensitive to noise. Recently, different types of entropy algorithms have been utilized for the analysis of EEG signals for detecting AD, MCI, or epilepsy (Kolekar & Dash, 2015). These algorithms include spectral entropy (Staudinger & Polikar, 2011), approximate entropy (Hornero, Abásolo, Escudero, & Gómez, 2009), sample entropy (Hornero et al., 2009; Timothy, Krishna, Menon, & Nair, 2014), Kolmogorov entropy (Grassberger & Procaccia, 1983), Tsallis entropy (Zhao et al., 2007), multiscale entropy (Hornero et al., 2009), permutation entropy (Timothy et al., 2014), and WPE (Deng et al., 2015). In addition to these features, some studies included more than one feature like ZCR, spectral centroid, spectral roll off, and spectral entropy with FD in order to increase the sensitivity and specificity of dementia diagnosis (Henderson et al., 2006; Staudinger & Polikar, 2011).

MI is the shared information between the two variables X and Y and is derived from the information theory. It estimates the probability density distribution (PDD) and joint PDD of two-time series and measures the statistical independence between two-time series by calculating various entropies.

$$I(X;Y) = \sum_{x,y} p_{XY}(x,y)\log\frac{p_{XY}(x,y)}{p_X(x)p_y(y)} = H(X) - H(X|Y) \qquad (3)$$

Here $p_X(x)$ and $p_Y(y)$ are the marginal PDD, $H(X)$ and $H(Y)$ are the entropy and conditional properties, respectively. MI is divided into two types: cross MI, which measures linear and nonlinear dependence, and auto MI, which measures the dependencies between single-channel EEG and the same EEG with some specified time delay. A recent study showed decreased MI in the frontal and right anterior temporal regions indicated less corticocortical connections in AD patients (Jeong, Gore, & Peterson, 2001). One study revealed that MCI subjects found lower theta frequency of MI during a task than normal subjects and proved that the connection between the parietal and occipital lobes for age- and disease-related changes could be detected using CMI analysis (Liu et al., 2012). Like Granger casualty, permutation conditional mutual information (PCMI) is used to measure coupling strength and direction between two EEG signals. This is a better feature than Granger casualty for recognizing the coupling direction of unidirectional or bidirectional EEG signals (Li & Ouyang, 2010). Some recent research has shown the superiority of PCMI in analyzing MCI and epilepsy EEG data (Li, Liu, & Ouyang, 2013; Wen et al., 2016). A recent study proved that MI is a more important responsive factor in detecting MCI compared to coherence (Vyšata et al., 2015). In addition to these, there are some features used to analyze synchronization between two or more EEG signals, such as S estimator (Dauwels, Vialatte, Musha, & Cichocki, 2010), stochastic event synchronization (Dauwels, Vialatte, Musha, & Cichocki, 2010), and graph theory (Stam, Jones, Nolte, Breakspear, & Scheltens, 2007).

Table 2 demonstrates the latest work done in the area of dementia diagnosis using different cognitive tasks. There are many previous studies available that use the cognitive task in work but that did not acquire the related EEG signal for the task. Staudinger and Polikar (2011) studied a few EEG features methods, such as EEG spectral analysis, coherence, and complexity, along with corresponding cognitive functions, to diagnose AD. Their investigation was an ERP study with auditory stimulus. The decline in resting-state alpha waves shows early dementia. The alpha wave in cognitive task ensure that the patient is in the awake state and not drowsy

(Staudinger & Polikar, 2011). Mcbride et al. (2014) acquired EEG data via a 10-min finger tapping test (FTT) performed by 48 subjects, when subjects were counting backwards, and when they were in a resting state. Relative spectral power, additional spectral features, spectral power ratios, entropy/complexity features, and first derivative features were extracted in this study (Mcbride et al., 2014). Reyes-Coronel et al. (2016) used the Boston naming test on subjects with rapid cognitive decline (RCD) and extracted many EEG features such as Shannon and TE, Granger causality and listed in Table 2. This study had a small number of cognitive decline subjects (Reyes-Coronel et al., 2016). Al-Qazzaz, Ali, Ahmad, Islam, and Escudero (2017) worked on a memory recall task with 35 VD, MCI, and healthy subjects. Recording length was 1 min and relative power and complexity measures were extracted using fuzzy neighborhood-preserving analysis with QR decomposition. Wang et al. (2019) worked with visual stimulus ERP and extracted one feature: directed transfer function of power (Wang et al., 2019). In recent work, Li et al. (2020) diagnosed MCI using 5 min of EEG in a cognitive reappraisal task. This work extracted various EEG features such as variance, RMS amplitude, Hjorth parameters, zero crossings, skewness and kurtosis, five EEG band Shannon entropy, singular value decomposition entropy, Fisher information, and SE.

Classification of dementia

During the classification process, the main aim is to distinguish MCI and dementia with high accuracy, which is essential for a diagnostic test. Classification is a way to identify the category or class of a new observation based on a training set of data that contains the characteristics. ML and DL techniques can be applied in almost every research problem for classification. ML techniques are chosen often and perform well where supervised learning is required. There are a few classifiers that are known for detecting MCI or AD, such as linear discriminate analysis (LDA), support vector machine (SVM), K-nearest neighbor (KNN), and neural network (NN).

KNN is a well-known classical ML technique to classify unknown subjects (Durongbhan et al., 2019; Sharma et al., 2020). The default 10-fold cross-validation procedure is implemented to increase the performance and reduce the fluctuation in ML algorithms. The collected EEG data were separated into N folders and the $N - 1$ folders were used for training the models. The rest of the data was used for testing, and this process continued for N times. Recently, KNN showed a better classification for dementia diagnosis with a maximum 92% accuracy in eyes-closed situation (Sharma et al., 2020). Decision tree (DT) is a decision-aided classifier with tree type models. DT is a flowchart type structure. DT has been implemented in a few studies of AD (Amezquita-Sanchez, Mammone, Morabito, Marino, & Adeli, 2019; Fiscon et al., 2018; Yin, Cao, Siuly, & Wang, 2019). EEG extracted features created the tree to categorize the subjects into two labels, and performance was measured by the Gini index (Yuvaraj, Acharya, & Hagiwara, 2018). C4.5 DT algorithm mostly applied as it can manage noisy datasets (Fiscon et al., 2018). The quality of the model was measured using a leave-one-out cross-validation method. DT was utilized for comparing with other classifiers in Yu, Lei, Song, Liu, and Wang (2020), Armañanzas, Iglesias, Morales, and Alonso-Nanclares (2016), and Yin et al. (2019).

SVM is a widely used classifier in EEG signal processing to classify neurodegenerative disorders and brain disorders like epilepsy (Al-Qazzaz et al., 2014; Kolekar & Dash, 2015; Sharma et al., 2019). It showed better accuracy (78%) than NN (60%–66%) for diagnosing AD in one study (Staudinger & Polikar, 2011). SVM is a supervised learning model widely used for regression and classification. It is often used to detect neurodegenerative disorders and is suitable for use when the data size is small or medium. The binary classifier selected to detect MCI at the early stage was chosen in Sharma et al. (2019), Khatun, Morshed, and Bidelman (2019), and Mcbride et al. (2014). SVM performance was also compared with a fuzzy logic-based method in Chiang and Pao (2016). Yin et al. (2019) developed a 3D evaluation method to select features to design an SVM classifier (Yin et al., 2019). The SVM considers the instances which will increase the margin to adjusting its hyperplane. Even the SVM could not solve the margin solidity problem, as the number of noisy instances in the EEG signal features was so large.

Table 3 lists the research work conducted on ML for dementia diagnosis. Most of the studies used SVM classifiers with 10-fold cross validation. One recent study used KNN with fivefold classification and achieved diagnostic accuracy of 98.57% and F-score of 98.57% (Li et al., 2020). Sharma et al. (2021) worked used FTT and obtained diagnostic accuracies of 97.12%, 94.86%, 94.74% for dementia, MCI, and healthy subjects, respectively. However, that was a binary classification for early dementia. Only four studies used multiclassification problem (Mcbride et al., 2014; Sharma et al., 2020, 2021). Al-Qazzaz et al. (2017) achieved 91.48% accuracy, 91.40% precision, and 91.48% sensitivity. These limited research findings and techniques motivate enhancement and provide an avenue for taking research in

Table 3 Literature review of ML work for dementia diagnosis.

State-of-the-art work	Classifier	Recording state	Group	Acc. (%)	Sen. (%)	Spe. (%)
Sharma, Kolekar, and Jha (2021)	SVM, 10-fold	EC	Healthy	90.23	84.92	92.67
			MCI	89.72	86.45	91.43
			Dementia	90.23	83.88	93.52
		EO	Healthy	94.66	89.38	97.11
			MCI	87.22	79.49	91.24
			Dementia	88.72	78.39	94.10
		FTT	Healthy	94.74	92.86	95.60
			MCI	94.86	93.77	95.43
			Dementia	97.12	93.41	99.05
Sharma et al. (2020)	*k*NN, 10-fold	EC	Healthy	89.58	85.14	91.61
			MCI	91.67	87.87	93.54
			Dementia	92.00	86.77	94.89
		EO	Healthy	90.36	83.33	93.53
			MCI	91.67	87.87	93.54
			Dementia	91.41	88.11	93.20
		FTT	Healthy	87.69	78.96	91.11
			MCI	87.69	78.87	92.51
			Dementia	88.62	87.37	89.33
		CPT	Healthy	91.87	90.46	92.52
			MCI	88.80	83.94	91.42
			Dementia	89.44	81.03	93.60
Li et al. (2020)	*k*NN, fivefold	Reappraisal task	Healthy vs. MCI	98.57	99.06	NA

Sharma et al. (2019)	SVM, 10-fold	EC	Healthy vs. MCI	79.50	73.00	85.00
			Healthy vs. dementia	83.70	90.00	78.00
			MCI vs. dementia	86.60	86.00	88.00
		EO	Healthy vs. MCI	84.10	86.00	81.00
			Healthy vs. dementia	82.00	82.00	82.00
			MCI vs. dementia	73.40	83.00	63.00
		FTT	Healthy vs. MCI	89.80	84.00	94.00
			Healthy vs. dementia	83.80	85.00	83.00
			MCI vs. dementia	84.00	89.00	78.00
		CPT	Healthy vs. MCI	73.90	63.00	82.00
			Healthy vs. dementia	87.90	88.00	88.00
			MCI vs. dementia	88.00	88.00	89.00
Durongbhan et al. (2019)	*k*NN, 10-fold	EC	AD vs. healthy	83.41	73.80	86.89
		EO	AD vs. healthy	83.32	72.57	87.52
Wang et al. (2019)	SVM, 10-fold	Visual oddball	VD vs. healthy	86.11	86.67	85.71
Al-Qazzaz et al. (2017)	SVM, 10-fold	EC	AD vs. healthy	84.61	100.00	80.00
		Memory recall	AD vs. healthy	91.48	91.48	NA
Reyes-Coronel et al. (2016)	SVM 10-fold	Boston naming test	RCD and non-RCD	80.9	80.00	81.10
Mcbride et al. (2014)	SVM, 10-fold	EC	Multiclass	79.20	NA	NA
		EO	Multiclass	83.30	NA	NA
		Counting with FTT	Multiclass	85.40	NA	NA
Staudinger and Polikar (2011)	SVM, sixfold	Auditory oddball	AD vs. healthy	77.61	NA	NA

this area to the next level. In one study, the NN accuracy was around 71% (Polikar et al., 2001). Dementia diagnosis using machine learning is currently an emerging research area (Buscema, Rossini, Babiloni, & Grossi, 2007). Many classifiers have been successfully used in other domains, such as a Bayesian classifier and hidden Markov model (Kolekar, 2011; Kolekar & Sengupta, 2004, 2015; Wu, Nagarajan, & Chen, 2016), which can be used for detecting dementia in future works.

Discussion

This chapter explored recent studies on using EEG signal data to detect dementia. Existing tools, like PET, MRI, and MEG, are expensive and time-consuming and thus there is increased attention on using inexpensive EEG data to assist in diagnosing neurological diseases. Among the many techniques used for detecting and classifying dementia, ML-based algorithms show the best accuracy. More specifically, SVM, DT, and KNN exhibited impressive performance for classifying EEG features. ML algorithms perform well when the dataset is not large. DL approaches were used in only a few studies but showed competitive performance. However, DL algorithms are computationally expensive and they perform better when the sample size is large. NNs did not perform well in any dementia and MCI classification. Future studies should focus on working collaboratively with hospitals and other researchers to create and share diverse and large datasets. Having a diverse and large dataset enables the model to be more accurate while classifying the subjects. ML algorithms also need the extracted features to be fed into the system as inputs. Raw data consists of artifacts and other noises, thus a good-quality noise-removing algorithm is important for achieving high accuracy. Conversely, DL algorithms are useful when the sample size is large and they do not need the extracted features to be fed into the system. DL algorithms extract features for themselves according to the requirements.

Conclusion

Early and automated diagnosis of dementia is a challenge. As such, future studies must investigate novel methods for detecting dementia with high accuracy. According to the studies presented in this chapter, ML algorithms with shallow architecture have performed well with small sample size, as it is always a challenge to find large datasets to use. Some studies were limited due to EEG data noise, and thus future works should aim to use larger datasets and implement noise-removing filters.

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