Chapter 3
The Role of EEG as Neuro-Markers for Patients with Depression: A Systematic Review

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Abstract Depressive symptoms may include feelings of melancholy, lack of interest, and difficulty remembering and focusing. The existing techniques of detecting depression need a lot of interaction with humans, and the findings are highly reliant on the knowledge and skill of the doctor doing them. Electroencephalography (*EEG*) is a potential tool that reveals interesting information that can be used in diagnosis and evaluation of human beings' brain abnormalities with excellent time resolution; however, detecting depression is a challenge for engineers and scientists to support personalized health care. However, *EEG* may provide an idea of cognitive decline toward depression classification. To create a neurophysiological diagnostic index for therapeutic use that is sensitive to the severity of depression, it may be possible to combine the *EEG* with other biological, cognitive markers, and imaging methods. The goal of the current study is to emphasize baseline *EEG* activity in depressed individuals, beginning with *EEG* signal collection and continuing through *EEG* data preprocessing steps for signal augmentation, linear and nonlinear properties. The subsequent focus will be on *EEG* signal extraction to account for the large swings of *EEG* signals, followed by classification approaches to differentiate the severity of depression. Therefore, the present review has examined the role of *EEG* signal processing and analysis in helping medical doctors and clinicians to determine suitable planning and optimal, more effective treatment programs.

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3.1 Introduction

The World Health Organization (WHO) estimates that 322 million individuals, or 4.4 percent of the global population, suffer from depression [1, 2]. It is one of the major mental illnesses that contribute to disability. Depression raises the chance of suicide significantly, which adds to the burden on patients, their families, and society [2] in addition to a number of physical problems.

Due to a lack of understanding, incompetent medical personnel, a lack of funding, and inaccurate diagnoses, a surprising 50% of patients with depression go untreated. A detailed understanding of the etiology and pathophysiology of the illness is urgently required, as is the development of a precise and effective method for identifying depression. If identified properly and with quick recognition, this disease can be easily treated [2].

One type of mental illness, known as major depressive disorder (MDD), has a significant impact on the patient, the healthcare system, and the economy Depression has been recognized as a substantial global source of impairment and disability among persons of working age [3], with a tendency to worsen physical and cognitive impairments and limit performance on professional duties. According to predictions made by MDD, adjusted life years in high-income nations would be considerably influenced by the disease by 2030 [4], which will cause major productivity losses due to presenteeism and absenteeism (failing to show up for work due to illness) (being present at work while sick). According to a 2003 World Health Organization study on mental health, employees with depression have an average yearly health care spend that is 4.2 times higher than that of a typical beneficiary [4–6].

To demonstrate the spatiotemporal feature of *EEG*, researchers have used non-invasive electroencephalography (*EEG*). When analyzing emotions, there are signs of sadness, seizures, Alzheimer's, Parkinson's disease, and more [2, 7–11].

In order to help the reader identify gaps, areas of agreement, key references, and other details that will help future research, this article highlights various gaps and difficulties in depression studies that have emerged in recent years while also providing a concise summary of each of these works. In order to do this, a methodical mapping process was undertaken, which included a review of the literature on non-invasive *EEG* depression markers that was mainly published between 2018 and 2022.

3.2 Brain Structure and Depression

The electroencephalogram (*EEG*) is a conductivity monitoring tool which records extremely irregular electrical activity of brain impulses and offers crucial information about various areas of the brain [9]. It offers methods for capturing brain electrical activity over time that are both non-invasive and affordable [12]. It is extensively used for doctors to study how the brain works and to identify physical

disorders. Since *EEG* is reliable, it is also employed in *EEG* biometrics for *person* verification [8, 13–19]. Furthermore, the *EEG* method is the most accurate due to its simplicity and high *temporal* resolution when compared to other methods for detecting depression (such as audio [20], facial [21], and MRI [22]).

Both depression and bipolar illness are signs of a brain problem. The aberrant structure of *EEG* signals manifests as variances in signal patterns for different patient states, allowing for the exact diagnosis of brain disorders, and the *EEG* responds to the biotic activities of the brain [9]. Fine contrasts between the chaotic and composite nature of normal and sad *EEG* data represent diverse brain processes in the depressive and normal groups that are challenging to show graphically [23].

3.2.1 Brain Structure

The brain is a remarkable organ that controls all bodily functions and processes environmental data. The brainstem, cerebellum, and cerebrum, all of which are located inside the skull, make up this structure [24]. One of the most crucial areas of the brain is the cerebrum. It is capable of doing complex tasks such as predicting touch, visuals, audio, speaking, mental skills, training, and correct motion control. The cerebrum is divided into two hemispheres, each of which has its own fissures and governs the opposing side of the body. Each hemisphere has four lobes: frontal, temporal, parietal, and occipital. The frontal lobe is in charge of consciousness, processing complex inputs as well as the senses of sound and scent are within the purview of the temporal lobe, the parietal lobe is in charge of managing objects and processing sensual information, and the occipital lobe is in charge of processing information related to the sense of sight [25]. The voltage differential between a scalp electrode and an ear lobe reference electrode is isolated during *monopolar* recording. On the other hand, *bipolar* electrodes record the voltage variation between two scalp electrodes [23].

3.2.2 Depression Types

There are several different types of depressive diseases Fig. 3.1. It's helpful to be aware of the many illnesses and their distinctive symptoms because symptoms can range from mild to severe [26].

3.2.2.1 Major Depression Disorder (MDD)

Major depressive disorder (MDD), one of most prevalent kind of depression, is characterized by a pervasive sensation of melancholy. Depressed mood, decreasing interests, diminished cognitive ability, and vegetative signs such irregular eating and

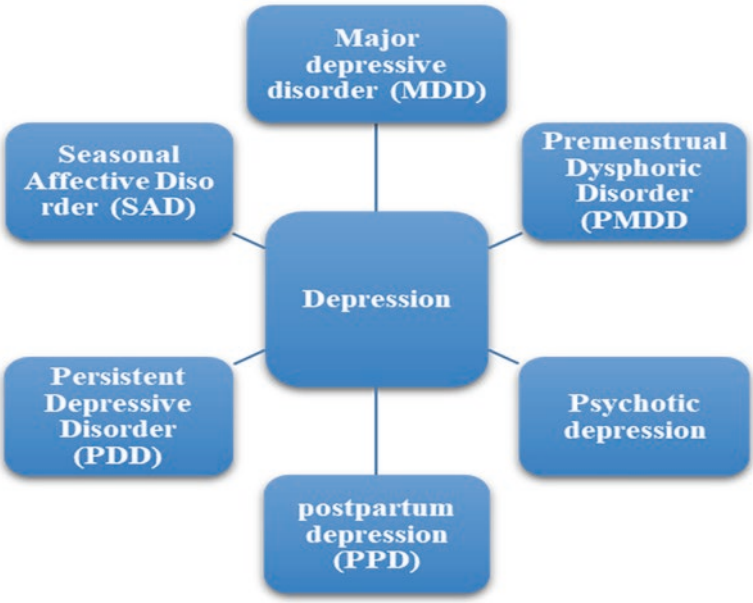

Fig. 3.1 Depression types

sleeping schedules are the hallmarks of MDD. One in six persons will experience MDD at some point in their lives, which affects almost twice as many women as males [26].

3.2.2.2 Premenstrual Dysphoric Disorder (PMDD(

Premenstrual dysphoric disorder is now considered to affect 3 *to* 8% of women of reproductive age who fit the rigorous criteria (PMDD).Studies show that the number of people who have clinically severe dysphoric premenstrual disorder is likely to be higher. Even if a woman doesn't have more than the arbitrary number of five indicators on the PMDD list, 13 to 18 percent of women of childbearing age may be unable to work or feel uncomfortable because of premenstrual dysphoric symptoms [27].

3.2.2.3 Psychotic Depression

The intensity of major depression was once thought to range from mild to severe, with psychotic depression being at one extreme. Experience gained later showed that psychosis is a distinct characteristic that may coexist with mood disorders of various degrees of severity. Poorly understood are trauma-related temporary or mild

schizophrenia, emotional incongruent features, and psychotic symptoms. While much is understood more about effects of extreme mood delusions and hallucinations on the progression and responsiveness to treatment of depression, there is still more to learn [28, 29].

3.2.2.4 Postpartum Depression (PPD)

The phrase "postpartum depression" refers to a wide range of mood disorders that arise after a baby is born. It's important to distinguish between the two because they may require quite different treatment options or none at all. Postpartum depression (PPD) affects 10–15% of new moms, however many instances go unreported [30]. Postpartum depression should not be confused with postpartum blues, which are transitory mood symptoms that occur within the first week to ten days following birth and normally go away within a few days [31].

3.2.2.5 Persistent Depressive Disorder (PDD)

There are four diagnostic subgroups for persistent depressive disorder (PDD), which is defined as a depressed illness lasting at least two years (dysthymia, chronic major depression, recurrent major depression with incomplete remission between episodes, and double depression). In the Western world, persistent types of depression account for a considerable number of depressive disorders, with lifetime prevalence rates ranging from 3 to 6 percent [32].

3.2.2.6 Seasonal Affective Disorder (SAD)

Seasonal Affective Disorder (SAD) is a recurrent major depressive disorder with a *seasonal pattern* that often begins in the fall and lasts through the winter. The "winter blues," also known as S-SAD, is a subsyndromal variation of SAD. SAD is less likely to cause depression in the spring and early summer. A low mood and a lack of energy are the most common symptoms. Females, those under the age of 35, those living far from the equator, and those with a family history of depression, bipolar disease, or SAD are the most vulnerable [33].

3.2.3 Effect of Depression on the Brain

Three regions of the brain are involved in memory and emotion regulation: the amygdala, located in the basal ganglia, the hippocampus, located in the temporal lobe (the frontal portion of the temporal lobe),are all affected by depression and bipolar disorder [34]. The hippocampus controls the release of the stress hormone

cortisol and preserves memories. When someone is depressed, their body releases cortisol; however, when too much cortisol is released and carried to the brain, it causes problems. In persons with MDD, prolonged exposure to high cortisol levels can prevent the growth of new neurons. It also affects memory issues by shrinking the neurons in the hippocampus. The prefrontal cortex, which is located in the *frontal lobe*, is important for emotion regulation, decision-making, and memory formation. When cortisol levels in the brain become too high, the prefrontal cortex shrinks. The amygdala is a structure in the temporal lobe's frontal region that controls emotional responses. Because of the constant exposure to a high cortisol ratio, the amygdala in depression and bipolar disorder patients grows larger and more active. Sleep difficulties and other activity patterns can result from an enlarged and manic amygdala, as well as erratic activity in other parts of the brain. Cortisol levels usually rise in the morning and fall at night. The cortisol ratio is usually higher in MDD patients, even at night [23].

3.3 Depression Diagnosis

Currently, the diagnosis of depression may be made using a variety of symptoms that aid physicians in evaluating many aspects of depressive functioning. The biomarkers, psychological evaluations, and physiological measurements are the most often utilized symptom-based diagnostic tools.

3.3.1 Biomarkers

A biomarker may be used to study the biology of depression as well as to predict or evaluate the risk of developing the disease, which are both necessary steps in the process of finding a *clinical* diagnostic or *therapeutic* intervention monitoring that may modify or stop the condition [35, 36]. A trait that can be reliably tested and evaluated as a predictor of physiological processes, pathologic processes, or responses to a *therapeutic* intervention is referred to as a biomarker [37]. Markers should not be mistaken with symptoms of a particular illness. Ideal candidates for the biomarker should be people who are at risk of depression and those who can recognize neuropathological processes even before a clinical diagnosis.

Figure 3.2 depicts the classification of biomarkers that Lopresti et al. [38] suggested. The classification of biomarkers comprises prognostic biomarkers, which are used to forecast how the illness will progress, diagnostic biomarkers, which are used to identify if a disease is present or not, therapy biomarkers, which may be useful in determining the best therapeutic option for a specific patient from a variety of therapeutic options, treatment-response biomarkers (also known as mediators), which are used to gauge treatment progress, and prediction biomarkers. Additional categories for biomarkers include trait, state, and endophenotype ones [39]. In

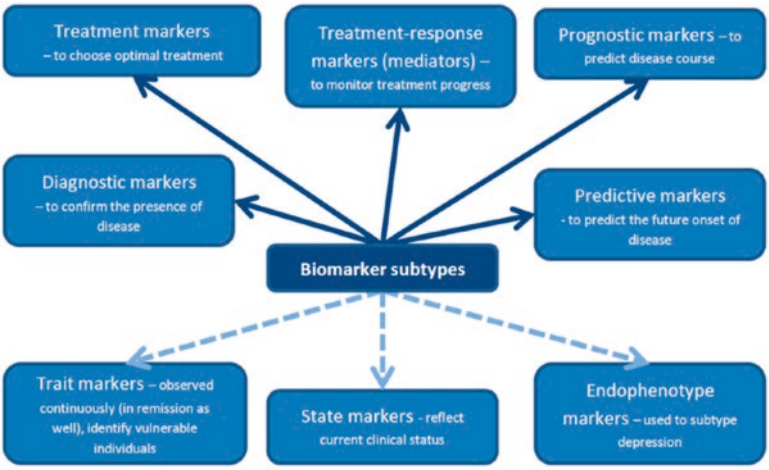

Fig. 3.2 Biomarkers subtypes

addition to the acute stage of the illness, trait biomarkers are those that can be reliably found before the onset of the disease or even in remission. Because of the final characteristic, they somewhat resemble predictive biomarkers [37].

3.3.2 Psychological Assessments

According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) published by the American Psychiatric Association (APA) [40], Depressive disorders include but are not limited to Major Depressive Disorder (MDD), Disruptive Mood Dysregulation Disorder (DMDD), Persistent Depressive Disorder (Dysthymia), Premenstrual Dysphoric Disorder (PDD), Substance/Medication-Induced Depressive Disorder (S/M-IDD), and Depressive Disorder Due to Other Medical Conditions (DDOC) [40, 41]. The genesis of MDD is linked to genetic, biochemical, hormonal, immunological, neurological, and environmental variables, as well as acute life events and neuroendocrine systems, according to [42]. While other varieties of depression have many of the same symptoms as MDD, they differ in a number of ways. DMDD, for example, is a *non − episodic* disorder that affects adolescents and teenagers. Obstinately irritable, displeased moods, as well as recurring temper outbursts, are symptoms. Dysthymia is a type of depression that lasts for a long time. During the last week or two before the menstruation begins, PDD produces extreme irritation and anxiousness [43]. The long-term type of MDD known as S/M-IDD (Drug/Medication-Induced Depressive Disorder) is brought on by or follows substance misuse. Depressive disorder caused by another medical condition might be brought on by ongoing diseases and persistent bodily suffering (DDDAMC) [23].

3.3.3 *Physiological Measurements*

Reducing the number of failed therapy trials could enhance MDD treatment. This outcome is expected if predictive measurements are used to accurately predict treatment results. The predictive measures must be sufficiently sensitive to changes in illness states, according to the definition [44–46]. These should also be suitable for therapeutic applications, like precise therapy forecasts for certain patients. The development of *EEG*/*ERP* metrics for assessing the efficacy of MDD treatments will be the main topic of this section. The *EEG* and *ERP* data that have shown significant associations with the *R* or *NR* subgroups will be explained, along with the values that were extracted from those data. Examples include *EEG* theta accordance, asymmetries, *antidepressant treatment response* (*ATR*) score, and alpha and theta activations [47].

For MDD patients it was discovered that the *ERP* elements, *P*300 levels, and latencies were related with therapeutic efficacy [47, 48]. The Loudness Dependence Auditory Evoked Potential (*LDAEP*) *ERP* type explains how one *EPR* component (*N*100/*P*200) varies when the auditory input becomes louder. It's thought to measure the amount of *serotonergic* neurotransmission in the primary auditory cortex. Lower *LDAEP* readings suggested higher chemical (serotonin) levels in the brain, and vice versa. The following subsections discuss related studies [47].

An auditory evoked potential (*AEP*) is an *ERP* component that is obtained by grand averaging numerous auditory stimuli of a single type *AEP*. *AEPs* have been found to have a beneficial relationship with cognitive capacities and brain auditory processes [49, 50]. In addition, a delay in the *P*300 component has been linked to depression [51]. Similar findings were reported in other investigations that only demonstrated a delay in *P*300 in MDD patients compared to controls [50, 52]. During *LORETA* analysis, there was also a drop in *P*300 intensity in the right hemisphere [53]. When compared to healthy controls, depressive individuals had longer *P*300 latencies for *visually evoked stimuli* [54]. The *P*300 delay returns to normal after 4 *weeks* of antidepressant use [47]. Furthermore, the normal *P*300 amplitude predicted electro-convulsive treatment response [55]. In contrast, there were no discernible variations in *P*300 amplitude between those who responded to the therapy, those who did not react, and the controls [56].

3.4 *EEG*-Based Depression Recognition Neuromarker

Neurological illnesses are challenging to accurately diagnose due to the absence of recognized biomarkers and the patient's subjectivity while responding to psychological evaluation questionnaires [57]. Research has examined the use of non-invasive *EEG* in order to search for biomarkers for the purpose of diagnosis or therapy prediction in light of this [58–61]. The search for non-invasive indicators of depression using *EEG* is crucial as it might help with more accurate illness

diagnosis, which is now done through questionnaires that are vulnerable to professional and patient subjectivity. But it's also problematic because depression has a vast variety of signs and symptoms [62] and a high level of comorbidity, particularly with anxiety [63], resulting in contradictory biomarker findings. Given the intricacy of depression, it's critical in order to keep up with the most recent findings of research on depression biomarkers [61].

EEG and *ERP* has role based prognostic biomarkers for MDD are discussed in [47]. Referenced *EEG* (*rEEG*) and *ERP* biomarkers *P*300, theta band activations, theta *QEEG* cordance, and asymmetrical alpha power [64]. The *P*300's potential clinical use as a marker for persons with present major depressive disorder in [65]. Previous studies have demonstrated that the Alpha and Theta frequency bands can provide information on the diagnosis and treatment of depression [66, 67], Gamma bands were not widely recognized in depression diagnosis [68].

In contrast, by giving some notable data on gamma pulses, [69] declares gamma waves as a depression diagnostic biomarker [70] *EEG* characteristics, including *linear* and *nonlinear* biomarkers and the Phase Lagging Index (*PLI*) at the patient's resting state, are used to identify depression. The *frontal Theta asymmetry* was used as a biomarker for depression by [67]. According to [71] multi-modal should be employed to diagnose MDD since depression affects not only mood but also psychomotor and cognitive processes [72]. looked at brainwaves as a possible biomarker for MDD risk assessment. The neural activities aren't just valuable in detecting depression, but also provide the groundwork for effective and dependable depression therapy. Compared to neuroimaging approaches, *EEG*-based depression biomarkers offer significant advantages [23].

3.4.1 EEG and the Brain

Due to the complex nature of electric brain activity that recorded as an *EEG*, it is necessary to characterize *EEG* fluctuations to understand its nature. Clinical *EEG* waveforms generally have physiological amplitudes of between (10 *and* 100) μv and frequencies between (1 *and* 100) Hz. According to their frequency ranges, *EEG* may be divided into five rhythms.

Alpha waves (α) are rhythmic waves that occur in awake, relaxed adults with their eyes closed and are associated with intelligence, memory, and cognition [73]. They have a frequency range of (8 *to* 13) Hz and a normal voltage range of (20 *to* 200) μV, and they vanish in pathological conditions like coma or sleep [74]. It is visible at the back of the head and reflects activity in the *frontal*, *parietal*, and *occipital* regions of the scalp [75].

Beta waves (β) have smaller amplitudes ranging from of (5 − 10) μv, and frequencies that are greater than those of waveforms, in the range of (13 − 30) Hz [73]. Records from the *frontal* and *parietal* lobes of the scalp [75].

Theta waves (θ) have a frequency range of (4 *to* 7) Hz and are most prevalent during sleep, as well as during emotional stress, arousal in adults and older children,

and idleness. It has an amplitude range of (5 − 10) μv and is recorded from the scalp's *temporal* and *parietal* area [73]. Based on their activities, people exhibit two different forms of *theta*. It has been connected to endeavors including concentration, focus, mental effort, and stimulus processing [75].

Delta waves (δ) have an amplitude range of (20 – 200) μv and a lowest frequency of less than 3.5 Hz. Deep sleep, infancy, and severe organic brain illnesses are times when it happens [73].

Gamma waves (γ) have frequencies between 30 *and* 100 Hz [73]. In the case of *cross − model* sensory processing, during *short − term memory* to recognize noises, objects, and tactile sensations, and in the pathological situation brought on by cognitive decline, especially as it related to band [75] recordings from the somatosensory cortex were made.

It is interesting to note that *alpha* and *beta* wave activities rise linearly throughout the lifespan while *delta* and *theta* wave activities decrease with age [76]. *Delta* current density and glucose metabolism have an antagonistic connection in the event of cerebrovascular illness, such as stroke, and this relationship changes as a result of depression in the sub-genual prefrontal cortex [77].

An individual's morphological *EEG* when they are healthy, *K − complex* is transient complex waveforms that have amplitude of about 200 μv and a slow frequency of 14 Hz. During sleep, it happened suddenly or in reaction to a quick stimulation and was linked with sharp components [78, 79].

Lambda wave is a monophasic, positive, sharp waves with an amplitude of less than 50 μv appeared posteriorly in the occipital lobes. It has to do with eye movements and visual exploration together [78]. *Mu* rhythm is located in the middle of the scalp, it appears as a cluster of waves with an arcade or comb form and amplitude less than 50 μv with a frequency range of (7 *to* 11) Hz. When there is thinking, preparedness, and contralateral movement of tactile stimulus, it manifests as blocks [78]. Spike is a transient, pointed peak, propagation duration (20 – 30) msec [78].

Sharp waves are transitory, sharp peak, propagation duration (70 − 200) msec [78]. Spike and wave rhythm consists of a series of surface sluggish, negative waves with a range of frequencies (2.5 − 3.5) Hz and amplitude of up to 1000 μv. It can sometimes manifest as complex waves and polyspikes [78]. Sleep spindle is an episodic rhythm occurred over the *fronto − central* area of the brain during sleep at a frequency of 14 Hz and an amplitude of 50 μv [78]. Vertex sharp transient, also known as a *V − wave*, is a response to sensory events experienced during sleep or awake and has an amplitude of roughly 300 μv [78].

3.4.2 Experimental EEG Protocol for Recognizing Depression

The *experimental* protocol for *EEG* depression detection includes a standard set of regulations, including the participants, subject selection criteria, *EEG* recording length, and other details.

In terms of the participants, there can be anywhere from one and two hundred, with a median of 30 people, depending on the study [41, 80–83], however other researches have been involved more than 50 participants [84–91]. Research with limited number of individuals have been illustrated challenges in determining the accuracy and in getting the final the findings [92–94].

Regarding participant gender, the majority of studies involve both male and female individuals [95]; however, only a small number of studies exclusively use female participants to detect severe depressive disorder using *EEG*. Men and women must both participate in studies since there is a chance that they will view depression in different ways [23].

Healthcare professionals and researchers frequently utilize the *Beck Depression Inventory* (*BDI*) [96] as a screening tool before making a diagnosis of depression or anxiety. Patients with MDD are chosen for this exam based on many *multiple − choice questions*. Patients having a *BDI − II* score of greater than 13 are categorized as depressive subjects. A high overall *BDI − II* score demonstrates the severity of depression. Many research employ the *BDI* to choose subjects [90, 92–94, 97].

The Diagnostic and Statistical Manual of Mental Disorders (*DSM − IV*), developed by the American Psychiatric Association (*APA*), has also been used in several research to quantify various mental illnesses [40]. A *DSM − IV*-based questionnaire is used as a preliminary *psychometric* test to evaluate depression in *EEG* -based diagnoses and most articles used it as a preliminary *EEG* test [90, 91, 98].

3.4.3 EEG Publicly Available Dataset for Depression Diagnosis

Due to the sensitive nature of the data and privacy and confidentiality concerns, few public datasets for *EEG* -based depression diagnosis are accessible.

The Healthy Brain Network (*HBN*) public data biobank was established by the Child Mind Institute [99]. H*BN*'s major goal is to create a data collection that correctly captures the broad range of variance and impairment that defines developmental psychopathology [99].

The National Institute of Mental Health has made the Establishing Moderators/Mediators for a Biosignature of Antidepressant Response in Clinical Care (*EMBARC*) dataset accessible to the general public (*NIMH*). Using *EEG* in the resting state and an algorithm for machine learning, it may be possible to determine the neurological signal of antidepressant medication response [100].

In the Depression public dataset, which is utilized in this study, motor activity recordings of 23 *unipolar* and *bipolar* depressed patients and 32 healthy controls are included [101].

Trans Diagnostic Cohorts [102] is assessed the effectiveness of brief transdiagnostic cognitive-behavioral group therapy (*TCBGT*) in treating individuals with

anxiety and depression. Instead of focusing on a single element, they conceptualize mental illness in terms of domain-wide inequalities [103].

Patient Repository for *EEG* Data and Computational Tools is a sizable, open-access dataset (*PREDICT*) contains *EEG* data [104]. There are numerous data repositories that house patient-specific information and imaging data. The Patient Repository for *EEG* Data + Computational Tool (*PRED + CT*) website is among the few that offer *EEG* -based patient-specific data [23].

3.4.4 Function of EEG *in Depression Detection and Classification*

For additional signal processing to extract significant indicators and depression classification, noise from the collected *EEG* dataset is need to be eliminated. The four basic phases in processing *EEG* signals are *EEG* signal capture, preprocessing, feature extraction, and classification.

3.4.4.1 *EEG* Signal Acquisition Stage

The *EEG* is a medical equipment that records data from the scalp using conductive material and metal electrodes and displays the electrical activity of brain neurons [105]. A $low-pass$, $high-pass$, and notch filter can be found in one of the most used *EEG* devices [106]. With a 50 Hz or 60 Hz notch filter, the usual frequency range for *EEG* recordings in depressed individuals is 0.3 Hz to 70 Hz [112]. The application determines the sampling frequency [23, 107]. The American *EEG* Society has recognized the worldwide federation's 10–20 system for recording the *EEG* of depressed patients while they are peacefully resting with their eyes closed [107–109]. For *EEG* recordings on depressive individuals, researchers have employed 19 electrodes [108–110].

3.4.4.2 Preprocessing Stage

Preprocessing is essential to distinguish vital information from tainted *EEG* signals since these artifacts reduce the quality of the genuine *EEG* signals [111].

A $low-pass$, $high-pass$, and notch filter can be found in the most widely used *EEG* device to enhance the performance of *EEG* signals [112].

A 12 *bit A/D* converter digitizes the signal to increase its accuracy. It is determined by the application whether the sample frequency is 128 Hz, 173 Hz, or 256 Hz. The *EEG* signal will then be captured, typed down, and presented on a computer screen for further examination [23, 107].

The frequencies of *EEG* signals and the majority of artifacts overlap. The *EEG* signal was contaminated by both physiological and non-physiological [113–117]. Because noise has a direct influence on the characteristics of the *EEG* signal, several signal processing algorithms have been developed to overcome this problem and obtain relevant data from the recorded *EEG* 3 signal

A collection of recorded *EEG* signals are divided into their sources using the blind source separation *higher order statistical* technique known as independent component analysis (*ICA*) [118–120].

To process non-stationary signals, such as *EEG*, the *Wavelet* transform (*WT*) method was developed [121–124].

Combining *ICA* and *WT* to create an $ICA - WT$ hybrid strategy was done by Nazareth et al. and other researchers [125]. Additionally, the WT can divide *EEG* signals into various sub-bands [126– 131]. Electrooculography (*EOG*) and muscular activity (*EMG*) artifacts have been successfully eliminated using the $ICA - WT$ approach [11, 132]. So, the signal is prepared for the following step (i.e., feature extraction stage).

3.4.4.3 Features Extraction Stage

To identify depression and create a relevant diagnostic index using *EEG*, feature extraction is used to the denoised *EEG* signal from the preceding stage. In this stage, linear and nonlinear algorithms are used to retrieve the pertinent data from the *EEG* of depressed patients.

3.4.4.3.1 Linear Spectral Features

It is simple to examine the power amplitudes for each band using linear spectral analysis, a direct information source acquired by *EEG* from the frequency domain. Alpha denotes mental sluggishness and relaxation [133, 134], whereas beta is related to expectancy [134], anxiety and introverted concentration [135]. Moreover, theta is considered for emotional processing [136, 137] and gamma is associated to attention, sensory systems [134] and may be related to mood swings [69]. However, delta is related to deep sleep [134].

The engineering way to diagnose depression is to explore essential biomarkers which would be applied to classification algorithms using power spectral features [138–140].

Recent research by Lee et al. [141] indicates that depressive individuals have lower beta waves in the central-left side of the brain than emotionally stable individuals and greater alpha waves on the left side of the brain. Last but not least, Dolsen et al. [142] found that depressed participants who had suicidal thoughts showed greater alpha activity during the whole night of sleep compared to those who had low suicidal thoughts.

Band power has thus been extensively examined and is simple to incorporate into classifiers that distinguish between depressed and healthy people. Regarding this, Fitzgerald evaluated some data in a high impact research [69] that suggests monopolar depressive individuals have elevated gamma activity.

On the other hand, although additional research is required to fully understand the role that delta and theta waves play in depression, they do appear to be worthy of consideration [138, 143]. Regarding theta, it appears to be a useful characteristic in diagnostic tools [139, 140, 144], but nothing is known about the mechanics underlying it. Furthermore, the beta wave appears to be more correlated with the anxiety and ruminative thoughts that are prevalent in depressed patients but may not be as critical for a precise diagnosis [61].

3.4.4.3.2 Nonlinear Features

Since many years ago, nonlinear dynamic methods have been extensively employed to examine the *EEG* signal. The *complex dynamic* information that is reflected from the cerebral cortex and captured by *EEG* devices has been studied by researchers using *EEG* [145, 146]. Brain behavior can be categorized as nonlinear because brain neurons are regulated by nonlinear phenomena including threshold and saturation processes [147, 148].

The Correlation Dimension (*CD*) and Maximum Lyapunov Exponent are the first nonlinear approaches that were used to analyze *EEG* in order to quantify depression based on *EEG* data as biomarkers (*MLE*). In order to determine how many independent variables are required to characterize a dynamic system, Grassberger and Procaccia adopted the *CD* method in 1983 [144, 149]. The *CD* method indicated the degree of freedom of a signal, with lower values indicating a reduced degree of unpredictability in the signal. On the other hand, Wolf used *MLE* as a dynamic metric to assess the adaptability of the system in 1985 [150, 151]. Fractal dimension (*FD*), Lempel-Ziv Complexity (*LZC*), which measures a signal's complexity and was first developed by Lempel and Ziv in 1976, can be used to predict the early identification of depression [152, 153]. It is shown that sad people have generally lower LZC values. In addition, Higuchi's Fractal Dimension (*HFD*), proposed by Higuchi [157], reveals the fractal dimension of a signal [89, 154] and Detrended Fluctuation Analysis (*DFA*), presented by Peng et al. [156], indicates long-time correlations of the signal [58]. Entropy approaches, such as sample entropy (*SampEn*) and Kologorov entropy, Tsallis Entropy (*TsEn*), approximation Entropy (*ApEn*), *SampEn*, and multiscale Entropy (*MSE*) [148, 158–163], have been used to address the complexity or irregularity in the system's capacity to generate information.

Researchers [47, 140] have used *nonlinear* features, such as *DFA*, to train a classifier and discriminate between healthy and depressed people. In comparison to healthy persons, depression significantly lowers *DFA*, according to Bachmann et al. [154].

In terms of signal complexity, HFD tends to be greater in depressed brains [58, 154], indicating a complex signal consistent with lower DFA findings.

The results utilizing DFA and HFD are consistent with the *CD* signaling a chaotic signal. Regarding LZC, it appears that the methodology may have skewed the findings because Kalev et al. [155] used a multiscale approach and observed various effects depending on the frequency whereas Bachmann et al. [154] found no difference.

3.4.4.4 Dimensionality Reduction Stage

Principal Component Analysis (*PCA*) [164] is one of many techniques that may be used to do dimensionality reduction in order to choose the ideal collection of features for automatic depression detection [165–167]. H. Cai et al., however, have utilized four feature selection techniques for this purpose, including Wrapper Subset, Correlation Attribute, Gain Ratio Attribute, and PCA [168].

The strategy of minimal-redundancy-maximum-relevance feature selection has been used in [149]. Additionally used in [169] is the sequential backward feature selection (SBFS) algorithm, while [170] applies differential evolution, a population-based adaptive global optimization algorithm.

3.4.4.5 Depression Classification Techniques

EEG is a very accurate classification method whose accuracy is directly connected to the quality of extracted features, and dimensionality reduction and classifiers are proposed to enhance *EEG* classification. Because of its accuracy and applicability in various research, linear Discriminant analysis (*LDA*) and Support Vector Machine (*SVM*) classifiers are the most prominent approaches used to categorize brain illnesses such as dementia and epilepsy [165, 166].

Different categories of machine learning based algorithms have been explored for *EEG* based depression diagnosis such as *SVM* based classifiers (Least Square-Support Vector Machine ($LS - SVM$) [171], *SVM* with different kernels [168], Linear and Quadratic Discriminant analysis based classifiers (*LDA*) and (*QLDA*) respectively, Ensemble architectures (*Bagging*, Rus-Boost (*RB*), GentleBoost (*GB*), and Random Forest (*RF*)), Logistic Regression (*LR*)), *K*-Nearest Neighbors (*KNN*) and its variants, Tree-based (Decision Tree (*DT*), *J*48, complex-tree), and others (Gaussian Mixture Model (*GMM*), BayesNet) [98, 168, 169, 172, 173].

3.5 Discussion

The literature has been used in this study to distinguish between the various depression- based *EEG* subtypes. Large-scale research is needed to discover trustworthy biomarkers that can aid in the diagnosis of depression, which is seen as a significant clinical challenge. Recent studies have looked into the potential for linear and nonlinear *EEG* -based biomarkers to be a distinguishing factor between various MDD episodes and depression severity scales.

The accurate sub-types of depression are the next significant challenge for depression-based *EEG*. Although it was a good effort, none of the machine learning models worked the best for all patients. Therefore, employing *EEG* -based data-driven methods, the answer to this significant issue can be investigated.

There has been a lot of interest in the identification and diagnosis of depression. Combining reliable markers with diagnostic criteria could achieve this. The detection of both episodes and subtypes of depression may be aided by neuropsychological tests and biomarkers evaluated against several depressive signs. We desperately require a marker for diagnosing depression that is precise, specific, and economical. *EEG* is a desirable technology for the early diagnosis and categorization of depression kinds and stages due to its low cost and non-invasive nature. The use of *EEG* as a neuro-marker to aid in the diagnosis of depression was the main topic of this review. Neurologists' subjective training makes it difficult to assess an *EEG* objectively, which leaves room for error. Additionally, it takes a lot of time and might not be able to pick up on little *EEG* changes, whereas computerized *EEG* signal analysis could streamline medical professionals' tasks and aid in more objective decision-making. Table 3.1 compares *EEG* acquisition devices, preprocessing, feature extraction, dimensionality reduction, and classification techniques used in research to diagnose depression.

In fact, BPFs and notch filters have been employed extensively in the preprocessing step [154, 174]. As shown in Table 3.1, [168, 171] frequently employs linear spectral components such as power *gamma*, *beta*, *alpha*, *theta*, and *delta*. *Nonlinear* entropy investigations, however, have produced good performance findings [170, 175].

They used a combination of classification algorithms to see if they could enhance the performance, sensitivity, and specificity of the best clinical diagnosis for early detection and classification of depression, based on its applicability in a variety of disciplines and empirically strong performance. *SVM*, on the other hand, is the most widely used machine learning-based algorithm that produces great performance outcomes for diagnosis [171] (refer to Sect. 3.1). *KNN* technology is widely used and produces excellent results. For the aim of classification, probabilistic models like *LR*, for instance, have received a lot of attention. *DT* is the most used algorithm for tree-based classifiers. Overall, *SVM* and *KNN* perform the best in terms of multiple performance measures, getting good classification results (around 99 percent) in the majority of the experiments.

Table 3.1 Comparative approaches used in depression diagnosis form *EEG* -based signals

Studies	Preprocessing methods	Features methods	Dimensionality reduction technique	Classification	
				Techniques	Best results
X. Ding et al. [174]	Notch filter, BPF	FFT Absolute power of (*gamma*, *beta*, *alpha*, *theta*, *delta*)	---		
M. Bachmann et al. [154]	BPF	Spectral asymmetry index (*SAI*), Alpha power variability (*APV*), Relative gamma power (*RGP*), *DFA*, *LZC*	---	*LR*	*LR* (92)
M. Sharma et al. [171]	Notch filter	*DWT*, relative-wavelet energy (*RWE*), Wavelet-entropy (*WE*)	*t*-test	LS-*SVM*, Complex tree, *LD*, *LR*, *KNN*, bagged	LS- *SVM* (99.54)
H. Cai et al. [168]	BPF, Kalman	Relative and absolute *centroid* frequency, relative and absolute power, C_0, *CD*, entropy	Correlation-based Method, wrapper based method, *PCA*	*SVM* (RBF), RF, *LR*, *KNN*, DT	DT (76.4)
S. Mahato et al. [176]	BPF	Asymmetry and paired asymmetry from sub-bands (*gamma*1, *gamma*2, *beta*, *alpha*, *theta*, *delta*), *DFA*, *SE*	ReliefF	Bagging, *SVM* (kernels such as polynomial,	*SVM* (96.02)
H. Cai et al. [149]	FIR, Kalman with *DWT* adaptive-Predictor filter (APF)	Relative and absolute power, *Hjorth* parameters (*activity*, *mobility*, *complexity*), *Shannon* entropy, *SE*, *CD*, peak, *Kurtosis*, *Skewness*	Minimal-redundancy-maximal-relevance	*KNN*, *SVM*, Classification- tree	*KNN* (79.27)
H. Akbari et al. [177]	LPF	Recurrence phase space (*RPS*) + geometrical *nonlinear* features	*GA*, Ant colony optimization, Grey wolf optimization, particle-swarm optimization	*SVM* (RBF), *KNN*	*SVM* (99.30)

(continued)

Table 3.1 (continued)

Studies	Preprocessing methods	Features methods	Dimensionality reduction technique	Classification	
				Techniques	Best results
Y. Li et al. [170]	Notch filter, LPF, HPF	*AR* model + max-power spectrum density, and sum power, C_0, *CD*, Kolmogorov-entropy (*KE*), *Shannon* entropy, permutation entropy (*PE*), Lyapunov exponent (*LLE*), singular-value deposition entropy (*SVDE*), variance, mean-square (*MS*), mean of peak-to-peak (*P2P*)	Differential evolution	*KNN*	*KNN* (98.40)
H. Peng et al. [178]	*BPF*	Phase lag index (*PLI*) from full-band as well four other sub-bands (*alpha*, *beta*, *delta*, *theta*)	Kendall's tau coefficient	*SVM* (linear kernel), *KNN*, DT, NB	*SVM* (92.73)
J. Zhu et al. [175]	LPF, HPF	AR model + power-Spectrum density (*PSD*), *AR* model + max-power spectrum density, sum power, C_0- complexity (C_0), correlation-dimension (*CD*), Kolmogorov-entropy (*KE*), Shannon entropy, permutation entropy (*PE*), singular-value deposition entropy (*SVDE*), mean-square (*MS*), mean of peak-to-Peak (*P2P*)	Correlation feature selection	*LR*, *KNN*, RF, *SVM*, BayesNet, NB, J48	*KNN* (92.65)
R. A. Movahed et al. [169]	LPF, HPF	Synchronization likelihood (*SL*), Higuchi-fractal dimension (*HFD*), Detrended-fluctuation analysis (*DFA*), C_0-complexity (C_0), correlation-dimension (*CD*), Kolmogorov-entropy (*KE*), *Shannon* entropy, Lyapunov exponent (*LLE*), *Kurtosis*, *Skewness*, *DWT* + relative-wavelet energy (*RWE*), *Wavelet*-entropy (*WE*)	Sequential backward feature selection (*SBFS*)	*SVM* (RBF), *LR*, DT, NB, RB, GB, RF	*SVM* (99)

X. Li et al. [98]	BPF. Adaptive- noise canceller (LMS) algorithm	*AR* model + power-Spectrum density (*PSD*), *AR* model + activity of *theta*, *alpha*, *beta*, *Hjorth* parameters (*activity*, *mobility*, *complexity*),	---	Ensemble model	Ensemble model (89.02)
QuickCap™, brain products Inc., Gilching, Bavaria, Germany et al. [179]	BPF	Task-related common spatial-pattern (*TCSP*) + *WPD* + differential entropy (*DE*) from (*gamma*, *alpha*, *beta*, *theta*, *delta*), wide band-EEG	GA	*SVM*, *LR*, *KNN*	*SVM*
H. Akbari et al. [180]	Notch filter	*EWT* + centered-correntropy (*CC*) *alpha*, *beta*, *gamma*, *delta*, *theta*	---	*KNN*, *SVM* (*RBF* kernel)	*SVM* (98)

3.6 Conclusion

Electroencephalogram has been emphasized as a study tool and prospective neuro-marker for diagnosing depression and grading its sorts in this review by offering succinct details on brain activity and how it is altered by various depression types. It should be mentioned that the review has highlighted discoveries relating to depressive illness at times. The reason for this is because there is a far larger body of information on depression sickness. The analyzed datasets were typically small as well, necessitating additional study to support the promising findings. On the other hand, the electroencephalogram has received high marks from numerous studies for its value as a clinical evaluation tool in the diagnosis of depression. Because of its low cost and accessibility, extremely sensitive electroencephalogram -based detection of depressive episodes and subtypes categorization is a generally wanted screening strategy in clinical practice. It is a promising method that can be utilized to adapt or tailor the best treatment plans for depression sufferers.

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