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Overview of Acquisition Techniques Brain Signals in Human Identification and Disease Diagnosis: Applications and Challenges

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Abstract:
Electroencephalogram (EEG) signals refer to distinctive neurons' electrical activity, depiction that upkeep biometric recognition. Usually in biometrics, the acquisition protocol has been important for EEG-based biometric system performance. Various acquisition protocols brain signals like evoked potentials besides relaxation, motor and non-motor imaginary have shown and discussed. This study discusses the potentials for identifying an individual based on EEG signals and highpoint the challenges of employing brain signals as a biometric modality in disease identification. Also, to discuss diverse solutions for limiting and decreasing their effects . Finally, an overview of EEG biometrics investigations has presented with findings and conclusions. Through this study it found that sensor like electrodes is help to disease diagnosis to detection disorder of the brain or increased power of the lower frequency bands and a decrease of high frequencies of patient's brain.

***Keywords**: Biometrics, acquisition techniques , Electroencephalography , machine learning , Brain- computer interface.*

1.Introduction

In biometrics, there are a lot of bio-signals used and among these signals that are used in disease diagnosis , these include respiration changes, Electromyography (EMG). Blood volume pulse (BVP), electro-cardio-gram (ECG), Skin temperature, and Electro-dermal responses (EDR) [1]. Hence, the bio-signals for disease diagnosis is becoming an interesting domain for human-computer interaction. In this type of signals, it need to use Brain-computer interface(BCI). Usually Brain-computer interface has a communication between human brain and external device. BCI equipmenthas intensive care conscious brain electrical activity throughelectroencephalogram signals. It can detect thefeaturesof EEGthrough digital signal processing that the user produces to communicate.Also, it provides the feasibilities forenabling the physically disabled issues to accomplishnumerous activities.Consequently,It can enhance life qualityand productivitywith higher independence and reduced social costs [2]. Nevertheless, the challenge with BCI is to extract the relevant patterns, from the EEG signals produced by the brain each second.

Four foremost strategies havetaken into consideration for BCI system inputlike P300 wave

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of event related potentials (ERP), slow cortical potentials, steady state visual evoked potential (SSVEP) and motor imaginary[3].The goal of this study is togive a wide-ranginganalysis of brain signals elicitation process from patient's brain for the purpose of detection the lengths of different brain signals that indicate the presence of a specific disease like Alzheimer's disease , epileptic seizure , Parkinson's disease, …etc . Also the type of techniques used to extract data from the human brain and which is better. In addition challenges by creating a communication interface using brain signals for the purpose of detection of diseases and proposed solutions to reduce these impacts . In this paper, some medical things regarding the structure of the human brain and types of waves inside it are clarified.

The paper is structured as follows: Section 2: related works, Section 3 EEG Signals acquisition. Section 4: medicinal parts of EEG, Section 5 Challenges and suggested solutions, section 6 Result and Discussions , Finally, the conclusion is presented in Section 7

2. Related Works

In this section we will search several types of the Electroencephalography techniques used in biometrics. Specially using EEG signal as disease diagnosis.According to (Horvath Andras, et al, 2017)was proposed sensitivity of various length EEGs in detecting Alzheimer's disease. Analyzed (24)h EEGs of five patients. The recorded sensitivity of a 30-min, EEG-epochfor 8:00 and 16:00 times has been 0.0375 .

While Automatic epileptic seizure detection, by used EEG signals was implemented by (Zhongnan , et al, 2017). machine learning library of SPARK)was applied when used Genetic algorithm (GA) as feature extraction . The accuracy was 99% when used SVM as classification.

(Acharya U Rajendra , et al 2018) was applied Classification of seizure EEG signals .Performed 13 layers deep convolution neural networks .. Dataset obtained from 5 patients .Each record is a single channel, EEG signal with a duration of 23.6seconds .Accuracy was 88.7% when Ten -fold validation was implemented as classification .

Parkinson's disease diagnosis from, EEG signals was proposed by (Oh Shu Lih, et al, 2018) . A thirteen-layer CNN was applied . performance was 88.25% accuracy. during the recording session 14 channels was used . The users were asked to sit comfortably, in a quiet room without body movements .detection system for the diagnosis of Schizophrenia was proposed by (Oh Shu Lih, et al, 2019)
Convolutional neural system was applied to detection this disease, comprised of 14 patients (7 males: 27.9 ± 3.3 years, 7 females: 28.3 ± 4.1 years) . Data hasgotten by the standard International 10–20 System. The used electrodeshave been Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2 with 25 second and 6250 samples . In addition, the modelhas given classification accuracies of 98.07% for non-subject based testing .

3.EEG Signals acquisition

In biometrics, the human brain signals are feasiblyobtained throughby means ofdiversemethodslike invasive and noninvasive methods. The method that necessitates surgical intervention to implant electrode under the scalp this type called (invasive) method [4] . Usually, scientistshave a tendency toevade invasive method, because medical hazards andrelated ethical issues. But, noninvasive approach is contactless with no implanting of exterior objects into human's brain [5]. It need to use Brain-computer interface (BCI) to support the use of EEG brainwaves as biometrics for disease diagnosis or to help disabled to perform many activities. Figure 1 illustrates an overall framework of BCIor using EEG signals [6] .

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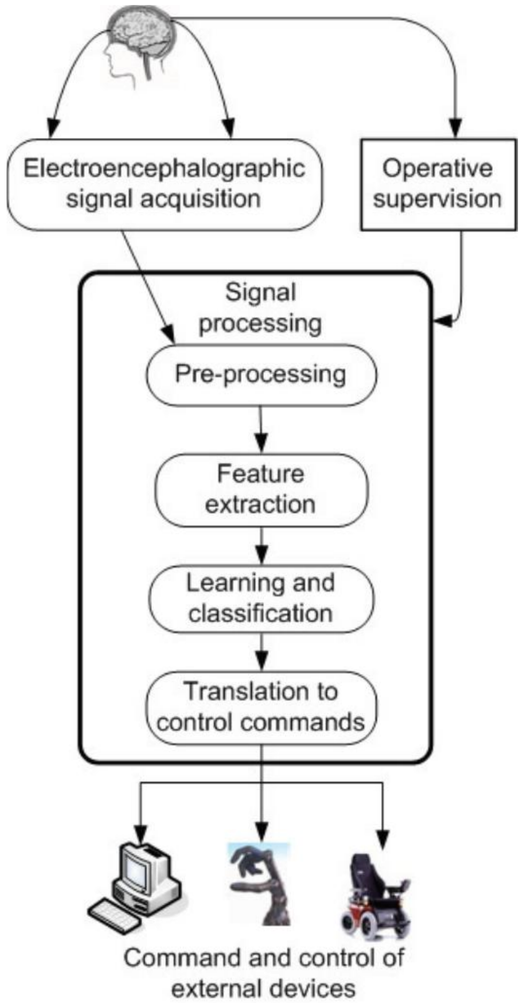

Figure 1 Block diagram of BCI

3.1 Techniques of acquisition EEG Signals

The performance of EEG signals using biometric system is subject to the appropriate design of the acquisition protocol. There are three type of categories when acquisition EEG signal from human brain and details have beendeliberated as follows [7]:

- Relaxation:

In this type of categories, a large number of researches motivated the use of this protocol when acquisition data from the human brain. Due to persons are generally asking for situated in an agreeable seat with the two arms resting which are requested to execute a couple of minutes from the resting situation with either a closed eye EC or an opened eyes EO [8]. The waves of Occipital alpha surrounded the duration of EC are the most instructed EEG encephalon signals.

- Motor/Non-motor Imaginary:

motor Imaginary can be described as the imaginative ability of awareness developments of the right-hand, left-hand, tongue, foot, etc [9]. Amid the engine symbolism, beta is for the most part appeared around the engine cortex, which can be utilized for the characterization of person's aim. EEG-based brain-computer interface (BCI) systems are comprehend either with the P300, steady-state visual evoked potentials (SSVEP) or, motor imaging. A P300 spelling device can be based on a 6 x 6 matrix of various characters displayed on the screen of computer [10]. The row/column spelling glows a complete row or a complete column of letters and symbols at once in a randomly order as depictedby Figure 2. The single character-speller glows only single symbol at a specific time.

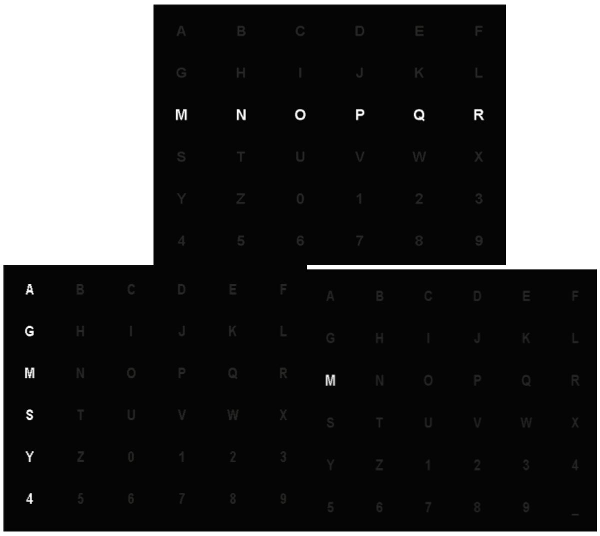
Figure 2 Left, mid panels: row/column speller. Right panel: one character speller

- Exposed to Stimuli (Evoked Potentials):

An evoked potential can be defined as recorded electrical feedback from a neural system after presenting the stimuli. It is classified into dualdissimilarclasses: Event-Related Potential (ERP) and Steady State Evoked Potential (SSVP)[11]. The SSVEP stimulant is accepted with a 12x12cm box (see Figure 3) prepared with 4 LED-

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clusters composing 3 LEDs each, moreover, four arrow LEDs were appended to show at which LED the user should consider during the practicing. The LEDs are constrained by a micro-controller connected with the PC through USB. The precise of the produced frequencies has to be highlyaccuratefor making the trait removing more authentic (frequency error is < 0.025 Hz) .

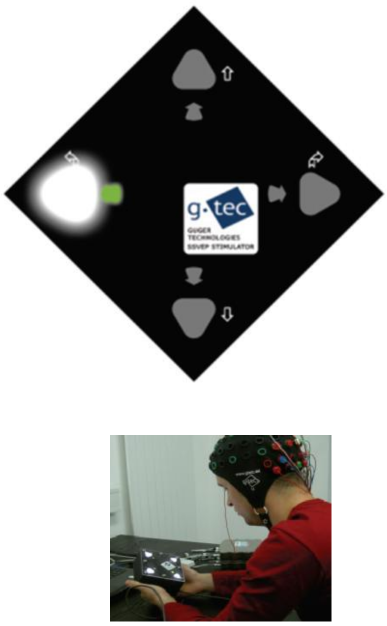

Fig. 3. SSVEP stimulation box and EEG recording

A variation of sensors for observing brain performance, and could be in obtaining the basis for a BCI. These involve electro-encephalography (EEG) and more incursive electro-physiological approacheslike electro-corticography (ECoG) besides feedbacks from persons' neurons through the brain, magneto-encephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and optical imaging (i.e., functional Near Infrared (fNIR)) [12]. The brain signals are provided by by means ofnumerous methods. It can be propagated as incursive and non-incursive technique. The incursive method needs operative interposition to embed electrodes underneath the scalp. Due to medical dangers, researchers incline to prevent incursive approach [13].

3.2 Placing Electrodes with a Cap

Human-Computer port can use various signals from the body so as to observe external devices. In addition, muscle activity (EMG-Electromyogram), eye motion (EOG Electro-oculogram) and ventilation as well brain goings-on (EEG-Electro-encephalogram) are feasiblyemployed as an input signal [14].

EEG electrodes are generally circulated on a scalp in the accordance to the global 10-20 electrode system. Therefore, the interval from the Inion to the Nasion has been firstly evaluated. In Figure 4, electrode Cz on the apex of the cap is moved precisely to 50 % of this interval. Show figure 4A. Figure1 4B explains a cap with 64 locations. The cap uses screw-able single electrodes to adapt to the depth and improve electrode resistivity. Each electrode has a 1.5 mm protection connector that is immediately connected to the bio signal amplifier [14].

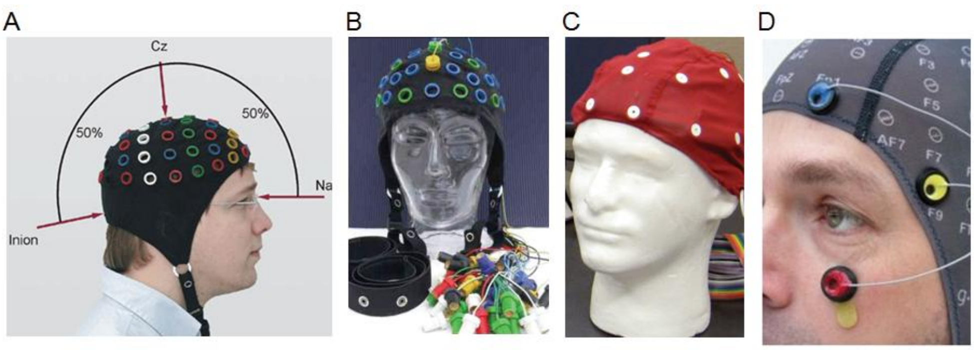

Figure 4 10-20 electrode placement

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EEG evaluations using single disc electrodes made of gold or Ag/AgClhave utilizedas in Figure 5. Gold electrodes have a worthy frequency feedback for EEG, EMG or ECG evaluations. There have beendual prime benefits of a single electrode system: (1) if one electrode collapses it is extracted directly. (2) Every electrode collage can be accomplished easily.

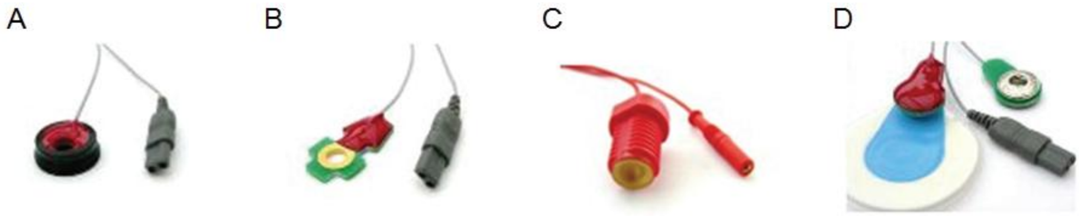

Figure 5Electrodes for measurements of EEG, ECG, EOG.

A: Active single electrode with multi-pole connector.
B: active gold electrode with multi-pole connector.
C: screw-able passive gold electrode to adjust location.
D: active ECG electrode with disposable Ag/AgCl Electrode.

The 10–20 system or global 10–20 system is an globally accepted method to designate and apply the position of scalp electrodes in the sequence of an EEG (Electro-encephalography) .Show figure 5 . One proved technique to put down electrodes by by means of such caps is as follows [15]:
Indicate the apex on the subject’s scalp by utilizing a felt-tipped pen or some other comparable method. Starting by locating the nasion and inion on the subject as shown in the figure 4A . Utilizing a measurement tape to find the interval between these dualpositions. The point half-way between the dual spots is the apex. Create a sign at that point for later remark. (Other 10–20 points can be positioned in a similar way.)
Indicate scalp locations for Fpz and Oz. The Fpz location is above the nasion 10% of the interval from the nasion to the inion. The Oz location is above the inion at the same interval.
Determine the Cz electrode on the EEG cap and put down the cap to location of the Cz electrode on the apex.
Keeping Cz firm, drop the cap onto the head [16]. While making sure that Cz doesn’t move, adapt the cap such that the Fz–Cz–Pz line is on the middle line; Fp1–Fp2 line has been horizontally, and at a stage of Fpz indicator; the O1–O2 line has been horizontal, and at a stage of Oz indicator [17].

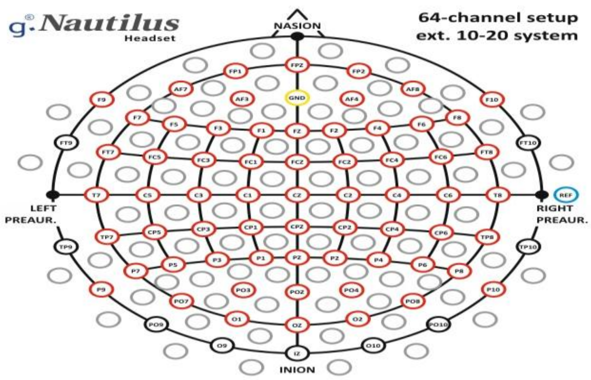

Figure 5 –international Electrode Placement

4. Medicinal parts of EEG

4.1 structuresof humanbrain

The human brain is an organ of three-pound that manage every parts of the body, explain information from out-side to enhance the soul and mind. Intelligence, memory, emotion, and creativity are parts of the many factors which have been controlled by the brain are protected in the skull.
The brain includes of brain-stem, cerebellum and cerebrum. The brain-stem is a transmission center between cerebellum and cerebrum which related to the spinal cord. The brain extradites information through five senses: sight, hearing, smell, touch, and taste. The nervous system can be classified into peripheral and central. The central nervous system

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(CNS) involves of the spinal cord and brain[18] . Whereas, the nervous system (PNS) is consists of spinal nerves that subdivided from the spinal cord and cranial nerves which in turn subdivided from the brain. The PNS involves the autonomic nervous system which controls essential section such as the secretion of hormones, ventilation, assimilation, and heart ratio. However, the purpose of the bony cranium is to protect the brain from injury. The shall comprises of 8 bones which merged together along suture-lines, these bones involve the one frontage, two temporal, sphenoid, two parietals, occipital, and ethmoid. Shown figure 6. The cerebrum is the largest portion of the brain that formulated of right and left cerebral hemispheres. It executes the higher section like construing touch[19]. vision and hearing as long as speech, intelligence, emotion, learning, and fine handle of motion. The cerebellum is positioned under the cerebrum, its operation is to co-ordinate muscle movements, preserve attitude and balance. The brain-stem comprises the mid-brain, pons, and medulla, it performs many automatic sections such as breathing, heart rating, body heat, wake and sleep cycle pattern, vomiting, and swallowing .Through our study of medicinal parts of human brain . Five frequency bands inside human brain . Explain it in detail in the result and discussion section

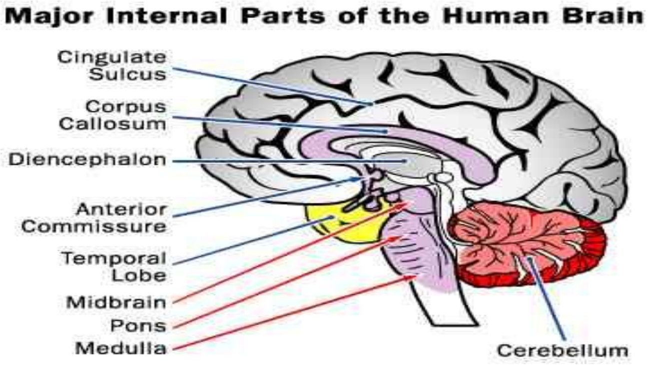

Figure 6 human brain

4.2 brain-lobes

Each side of the human brain comprises four lobes. The frontal lobe is significant for cognitive operations and control of volitional motion or activity. The parietal lobe handles information about body temperature, taste, touch and motion, while the occipital lobe is mainly in charge of vision. The temporal lobe controls memories, combining them with sensations of taste, sound, sight and touch [20].

Some of the many other functions the frontal (blue) . Show figure 7lobe plays in daily functions comprise: Production of speech and language, Some motor abilities, Comparison between objects, Constructing memories , Reward, seeking behavior and motivation-Managing awareness, including exacting attentionWhile Parietal lobe operations comprise (orange) is responsible in Cognition, Processing of Information, Touch Feeling (Pain, Temperature, etc.), Comprehending Spatial Orientation, Movement Co-ordination, Speech-Visual Perception, Reading and Writing, Mathematical Calculation

Main function of the occipital lobe is observing vision and visual operating [21] .This organ assists people to see and identify identifying objects that human looks at. It also assists people to distinguish and comprehend distinct colors. Its operation also comprises the capability to understand and differentiate between various shapes.The temporal lobes (green) of the human brain are responsible of a wide types of operations: The lobes handle memory, sound processing and facial recognition.Comprehending language (Wernicke's area), Remembrance , Hearing , Sequence and management .

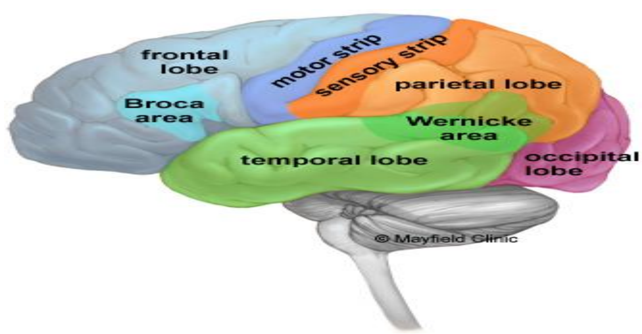

Figure 8 brain- lobes

5- Challenges and suggested solutions

5.1 Challenges

The challenges in diagnosing diseases(diseases that concern the human brain) through the use of BCI .These challenges are relevant to the training process classes of discrimination. In addition to relate to recorded electrophysiological features of the human brain signal thatcomprises non-linearity , noise , or high dimensionality .

5.1.1 Non-linearity

Through the complex brain structure ,EEG signals are better distinguished through nonlinear dynamic approach as compared to linear approach .

5.1.2. Noise

It stands for a huge contributor in the challenges facing the BCI technology and causes the nonstationarity issue. It includes unwanted signals, caused by alterations in electrode, placement and environmental noise[22] . Also there are several factors that help in the difficulty of distinguishing the underlying pattern when acquired signals, such as movement, signals created by eye movements, or blinking electrooculogram.

5.1.3 High dimensionality

Signals can be recorded from numerous channels for maintaining high accuracy based on the amount of needed information for describing various signalsincreases with the vectors dimensionality[23]. There have beennumerous feature extraction approaches have been proposed. Classifier performance will be influenced, only by the minoramount of distinctive traits instead of the entire recorded signals that may contain Redundancy. Due to they play an important, role in identifying features.

5.2 Suggested solutions to these problems

There are several solutions have been proposed to confront and limit, the influence of the earlierstated technical issues as in:

5.2.1 Noise removal: There are unwanted signals found in the case of obtaining signals from the human brain . Signal processing is either two way spatial time or frequency domains[24] . Using one of these ways help improve the signal . In addition Improving the signal to noise ration (SNR) of human brain signal . Independent Component Analysis indicates a way to increase or decrease the noise level for the purpose of improving the signal . While Frequency-band domain filtering can contribute in removing artifact and noise . In this way , additional electrodes that are used to detect eyes movement or muscles movement are not required .

5.2.2 Multilayer separation

In machine learning techniques contain several approaches or algorithms that can be used in Separability of multiple classes[25] . The aim of these methods to achieve higher performance and accuracy . In the next section , we will explain five different algorithms for machine learning such as (naiva bayes , Decision Tree , SVM, Meta Learning , Logistic Regression)

5.2.2.1 NaiveBayes: This technique is helpful for diagnosis disease , classification or forecasting of weather . It enhances the classification performance through eliminate the unrelated features . [26] . According to the features , naive Bayes classifiers can be used efficiently in a supervised learning [36]. In addition it takes less time with calculations and give a good performance . One other hand it is lazy , as they store entire the training examples . The Naive Bayes conditional probability can be written as

$$P(C_k|F) = \frac{P(C_k).(F|C_k)}{P(F)} \text{-------}(1)$$

Where vector $F = (F_1, F_2, \ldots \ldots F_n)$, n represent the independent feature

While probability $p(C_k|F_1, F_2, \ldots .. F_n)$ k is possible classes C_k

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5.2.2.2 Decision Tree: It can be defined as highlyfrequently machine learning techniques used in last years. This technique is in the form of a tree such as hierarchy for constructing classification trees[27] . Usually trees stand for a simple form in which the non–terminal nodes specifying the attribute tests, and the terminal nodes present, decision outcomes. In tree approach, it doesn't generate multiple outputs . Also, it is relativelysubject tonoise in the data . The process of decision trees is select the best highlights, for every decision hub, amid the development of the tree in view of, some all – around characterized criteria .

5.2.2.3*Support vector machine(SVM*): It stands for supervised learning algorithm as one of used classification approaches for different tasks . SVM method is suggested by Cortes and Vapnik [28]. The SVM has a single layer which depends on statistical operation. The action of the SVM is generally using core function to create a planefor carrying the data sets that are difficult to separate linearly into a huge dimensional space , and exploits the distance between classes [29].Many types of SVM approach such as Radial Basis Function, Linear , Polynomial , Sigmoid . Each of these types contains different mathematical and statistical operations for the purpose of making their own classification.

5.2.2.4 Meta Learning algorithm: Theyhave analyzed based on Correct Classification as well as Incorrect Classification and Time for building models. Various type of meta learning such as Ada-Boost , Logit- Boost , Bagging, Grading . Developed Adaptive boosting meta learning algorithm by Freud Yeave and Scapire[eee] With different algorithms to construct a "powerful" classifier . In Ada-boost may be less vulnerable to the problem of over fitting as compare to many learning algorithms .While building a boosting algorithm known as Logit- Boost by (Friedmome ,et al)[30] , it was applied by logistic regression to Ada-Boost method . Another type of Meta learning algorithm is bagging [31]. It a name derived from"bootstrap aggregating". This approach has used to improve unstable assessment or classification algorithm. Studies indicate that this algorithm help to produce and combine various classifiers through thesimilar learning algorithm for, the base classifiers. While Grading refer to algorithms that are examined. Centralconception of this algorithm is to predict whether the prediction for learning algorithm for, specific examples is right, or not. The process of training this algorithm is on the basis of one classifier for every actual learning, algorithms is being trained, which includes the actual examples, with class labels that encrypt ,whether this learner's forecast has beenaccurate on precise example .

5.2.2.5 Logistic Regression: This approach is based on statistical modeling technique . It has been widely used, in many fields like, social science and medical ,field . Usually logistic models are used to model the probability of class such as pass and fail , win and lose .There are many types of logistic Regression such as (polynomial regression , ordered logit , generalized linear model , mixed logit, binomial regression). The logistic Regression method is defined[32] by the following equations:

$$\mathrm{Logit}(P_1) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i \ldots\ldots (2)$$

Where β_0 is called intercept and $\beta_2 , \beta_2 , \beta_3 \ldots\ldots\ldots \beta_n$ are coefficients associated with the given explanatory variable $x_1 , x_2 x_3 , \ldots\ldots\ldots x_n$

One type of logistic regression is Binary Logistic Regression which can be applied to calculate the relationship between a categorical dependent variables and several independent variable through using probability scores as the predicted values of the dependent variables.

6. Result and Discussions

The objective of this study that disease diagnosis has been neededfor the reason that it might be cognitive function, compromise and accelerate

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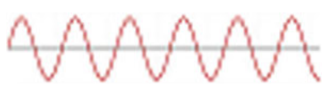
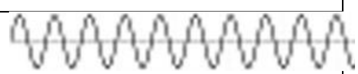
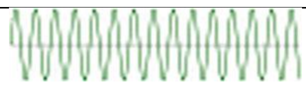
disease progression.Table 1 depicts the acquisition protocols implemented in the previousreported papersin addition to the database set up and system performances. All previous studies have used sensors. These sensors helps us to know the diagnosis of diseases , especially the accuracy rate is above 99% according to previous studies .

Table 1 previous studies by using sensors to disease diagnosis

NO	Author	Disease	Accuracy	Dataset	Year
1	(Horvath Andras, et al)[3]	Alzheimer's disease	-	Sensor EC/EO	2017
2	Zhongnan , et al)[4]	epileptic seizure	99%	Sensor ERP	2017
3	(Acharya U Rajendra) [5]	Seizure 's disease	88%	http://epilepsy.uni-freiburg.de/database)	2018
4	(Oh Shu Lih, et al)[6]	Parkinson's disease	88%	Sensor Emotive EPOC	2018
5	(Oh Shu Lih et al)[7]	Schizophrenia's Diagnosis	98.07%	Sensor	2019

Brain signals are obtained through three techniques like relaxation , Motor/Non-motor Imaginary or Evoked Potentials . The first one is better because a large number of researches motivated the use of this technique . Due to the person is sitting in a comfortable chair with either a closed eye or an opened eyes in a relaxed atmosphere without stimuli .These factors help to obtained the signals correctly .Through our study of brain signals , EEG signals are analyzed in two different ways: By frequency domain or analyze time domain .The method of analyzing the frequency domain is better than other . Due to analyzing different bands . It found that there are several waves such as (Delta, Theta , Alpha , Beta , Gamma) that appear on a human brain in many different situations . Table 2 illustrates Comparison of EEG frequency state and weave form .

Table 2 comparison between Brain-computer interface Signals [16]

Frequency band	**Scalp location placed electrodes**	**Range**	**Normally Mental State**	**Weave form**
Delta	High –amplitude weaves	0 HZ< F <4 HZ	Deep dreamless sleep in babies brain	
Theta	High –amplitude weaves	4 HZ< F <8 HZ	Signal is higher in young children Sleepiness in adult and teens	
Alpha	High in amplitude on central side	8HZ< F <14 HZ	Relaxed, Closing the eyes	
Beta	Low –amplitude weaves	14HZ< F <30 HZ	Normal ,relaxed	
Gamma	Somatosensory cortex	30HZ< F <100 HZ	Higher mental activities	

According to Challenges and suggested solutions, there are many challenges when use Brain-computer interface for the purpose of detecting human diseases, especially brain diseases. Diagram 1 refer to summarize challenges and proposed solution to reduce existing problems using different techniques.

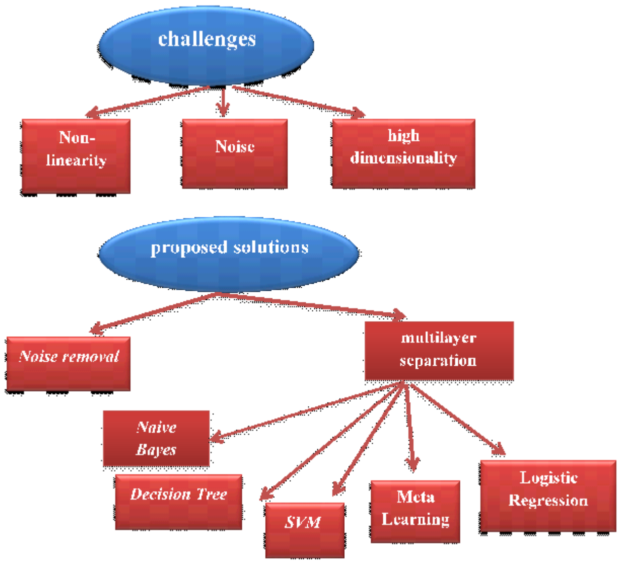


Diagram 1 challenge and suggest solution

7. Conclusion

EEG is one of the most active capturing techniques that can be utilized in bio-metrics because of its hardware devices evolution. It is a very unique, secure and cannot be replicated method. Besides that, EEG signals are biodynamic and possess a proof of aliveness for a particular individual. Thus, it cannot be duplicated like most of the other static physical biometric techniques . Brain Computer Interfacing provides a communication between brain and external equipment . Numerous studies have, included in this paper concerning the rising interest in BCI application fields like disease diagnosis . It also determines the various, devices used for capturing, brain signals. These recording devices haveclassified into dualgroupsof invasive and non-invasive. First type which necessitates implanting surgery, while second type as statedearlier, has been extensively spread due to its advantages. Medicinal parts of EEG and general structures of brain it was explained in this study . There are two methods used to analyze brain signals such as frequency domain or time domain . In addition Comparison between Frequency band (Delta , Theta , Beta , Alpha , Gamma) and the shape of each wave and its appearance .There are still ongoing challenges in this field to choose the best sensors and analyze signals in the best way to obtain better results for diseases diagnosis . Other challenges and suggestion solution by different algorithms it was discussed . Diagram1 illustrates these challenges and solutions .

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