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Brain Signal Analysis in Alcoholism

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Abstract - In this study, the magnitude and frequency spectrum in the electroencephalogram (EEG) were examined to address the classification possibility of alcoholism in the central nervous system. The pre-recorded EEG signals for chronic alcoholic conditions & control condition taken from the motor cortex region and methodologies used for feature extraction is Fast Fourier Transform, four Feature Real Power, Absolute Power, Peak Power Frequency; Median Power Frequency having five sub frequencies band (delta, theta, alpha.beta1, beta2) for each feature is extracted from the alcoholic condition as well as a control condition. These extracted features are classified by SVM and FLANN . The maximum classification accuracy is achieved with the EEG spectral of feature of PEAK POWER FREQUENCY in the THETA band in F3 channel (80%), by using SVM, and by using FLANN max accuracy is obtained in f3 electrode.

Keywords - Alcohol; Cerebral motor cortex; Electroencephalogram; Fuzzy C means clustering

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I.INTRODUCTION

1.1 EFFECTS OF ALCOHOLISM

Alcoholism is considered as a primary chronic disease characterized by impaired control over drinking. The symptoms commonly associated with alcoholism are: craving (a strong need); impaired control (the inability to limit); physical dependence (withdrawal symptoms such as nausea, sweating, shakiness, and anxiety when alcohol use is stopped after a period of heavy drinking) and tolerance (the need for increasing amounts of alcohol in order to feel its effects) [1]. Alcohol directly affects brain chemistry by altering levels of neurotransmitters the chemical messengers that transmit the signals throughout the body that control thought processes, behavior and emotion. Alcohol affects both “excitatory” neurotransmitters and “inhibitory” neurotransmitters.

Cerebral cortex: In this region, where thought processing and consciousness are centered, alcohol depresses the behavioral inhibitory centers, making the person less inhibited; it slows down the processing of information from the eyes, ears, mouth and other senses; and it inhibits the thought processes, making it difficult to think clearly.

Cerebellum: Alcohol affects this center of movement and balance, resulting in the staggering, off-balance swagger we associate with the so-called “falling-down drunk.”

Hypothalamus and pituitary: The hypothalamus and pituitary coordinate automatic brain functions and hormone release. Alcohol depresses nerve centers in the hypothalamus that control sexual arousal and performance. Although sexual urge may increase, sexual performance decreases.

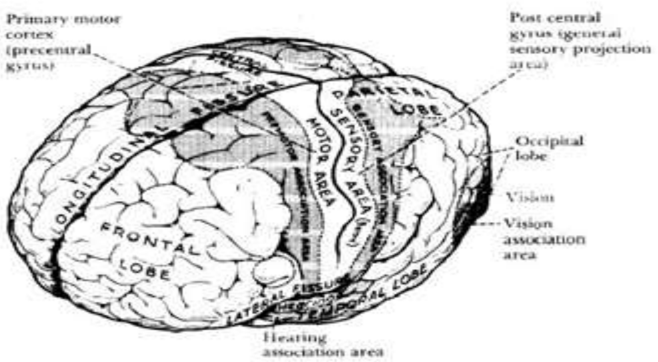

Fig1.1: internal structure of human brain

It is often difficult for doctors to decide which person to screen for an alcohol problem [2]. Person may complain about their digestion, pain or weakness, but never reveal their abuse of alcohol. A doctor who suspects the alcohol problem may ask a series of questions but denial is a hallmark in alcoholism. Blood and urine alcohol tests are not useful in diagnosing chronic alcoholism because the tests indicate consumption only at a particular instant of time. Thus, the aim of this study is to examine the utility of the EEG to detect the changes in brain electrical activity of alcoholic persons.

Bio signal: The term ‘bio signal’ is defined as any signal measured and monitored from a biological being, although it is commonly used to refer to an electrical bio signal. Electrical bio signals (bio-electrical signal) are the electrical currents generated by electrical potentials differences across tissue, organ or cell system like the nervous system. Typical bio-signal are ECG(electrocardiogram), EMG(electromyogram), EEG(electroencephalogram) and EOG (electroculogram). GSR(galvanic skin response) and HRV(heart rate variability) are also thought of as bio-signals, although they are not measured directly from electrical potentials differences.

Neuro-signal: Neuro means brain; therefore; 'Neuro-signal' refers to a signal related to the brain. A common approach to obtaining neuro-signal information is an electroencephalogram (EEG), which is a method of measuring and recording Neuro-signal using electrode placed on the scalp.

Two types of EEG montages used which are mono-polar and bipolar. The mono-polar montage collects signals at the active site and compares them with a common reference electrode. The common electrode should be in a location so that it would not be affected by cerebral activity. The main advantage of the mono-polar montage is that the common reference allows valid comparisons of the signals in many different electrode pairings. Disadvantages of the mono-polar montage include that there is no ideal reference site, although the earlobes are commonly used. In addition, EMG and ECG artefacts may occur in the mono-polar montage. Bipolar montage compares signals between two active scalp sites. Any activity in common with these sites is subtracted so that only difference in activity is recorded. Therefore some information is lost with this montage. so in this research we use mono-polar montage. Electrodes conduct voltage potentials as microvolt level signals, and carry them into amplifiers that magnify the signals approximately ten thousand times. The use of this technology depends strongly on the electrodes positioning and the electrodes contact. For this reason, electrodes are usually constructed from conductive materials, such us gold or silver chloride, with an approximative diameter of 1 cm, and subjects must also use a conductive gel on the scalp to maintain an acceptable signal to noise ratio. The FFT (Fast Fourier Transform) is a mathematical process which is used in EEG analysis to investigate the composition of an EEG signal. Since the FFT transforms a signal from the time domain into the frequency domain, frequency distributions of the EEG can be observed. EEG frequency distribution is very sensitive to mental and emotional states as well as to the location of the electrode(s). Two types of EEG montages are used: mono-polar and bipolar. The Mono-polar montage collects signals at the active site and compares them with a common reference electrode. The common electrode should be in a location so that it would not be affected by cerebra l activity. The main advantage of the mono-polar montage is that the common reference allows valid comparisons of the signals in many different electrode pairings. Disadvantages of the mono-polar montage include that there is no ideal reference site, although the earlobes are commonly used. In addition, EMG and ECG artifacts may occur in the mono-polar montage. Bipolar montage compares signals between two active scalp sites. Any activity in common with these sites is subtracted so that only difference in activity is recorded. Therefore some information is lost with this montage.

II. THE NATURE OF THE EEG SIGNALS

The electrical nature of the human nervous system has been recognized for more than a century. It is well known that the variation of the surface potential distribution on the scalp reflects functional activities emerging from the underlying brain [3]. This surface potential variation can be recorded by affixing an array of electrodes to the scalp, and measuring the voltage between pairs of these electrodes, which are then filtered, amplified, and recorded.

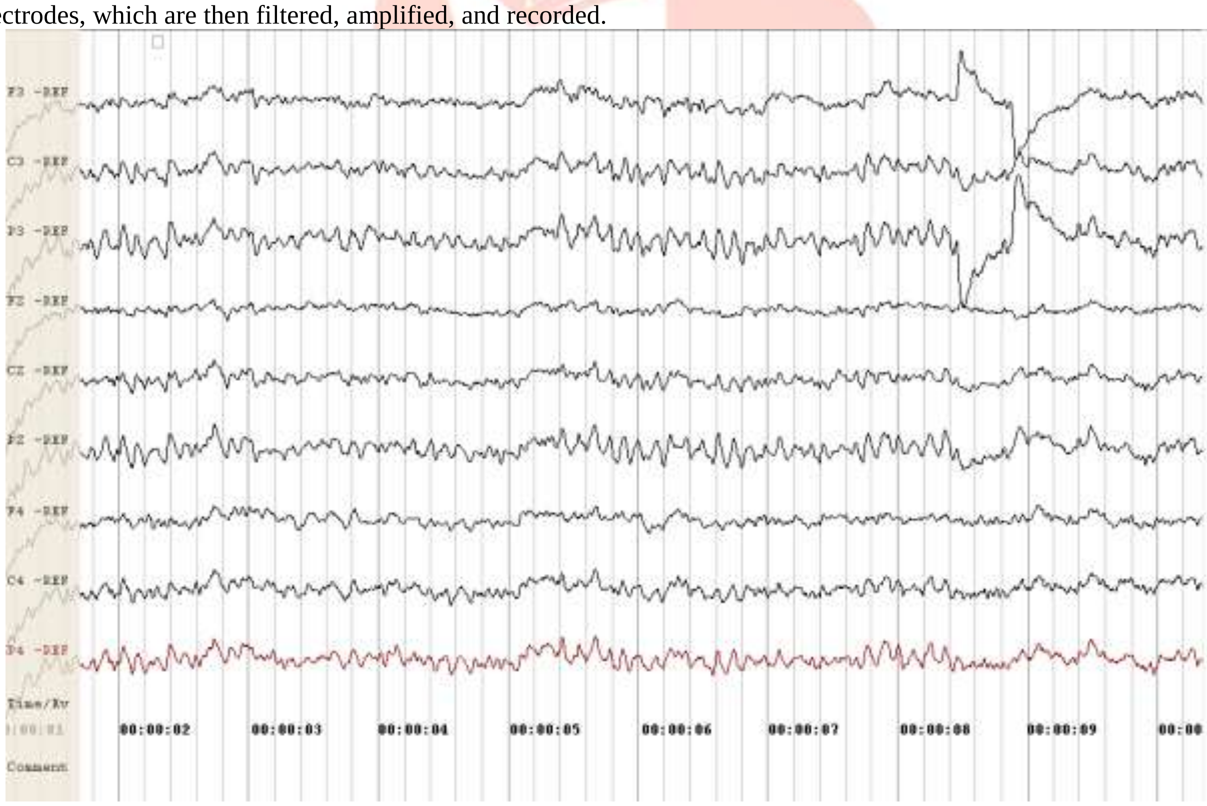

Figure2.1 A segment of a 9 channel EEG of a alcoholic subject

III. THE 10-20 INTERNATIONAL SYSTEM

3.1 Electrode positioning

10-20 international system is the standard naming and positioning scheme for EEG applications. It is based on an iterative subdivision of arcs on the scalp starting from craniometrist reference points: Nasion (Ns), Inion (In), Left (PAL) and Right (PAR) pre-auricular points. The intersection of the longitudinal (Ns-In) and lateral (PAL-PAR) is named the Vertex.

3.2 Nomenclature of electrode: P is parietal lobe, f is frontal lobe, c is central lobe, o is occipital lobe. Recording of EEG signal from 64 electrode, out of 64 electrode we use only 9 electrode (c3,c4,cz,f3,f4,fz,p3,p4,pz) . These electrode positioned in central lobe of our brain. Under literature review most affected in brain is central lobe in alcoholism so we use central lobe electrode.

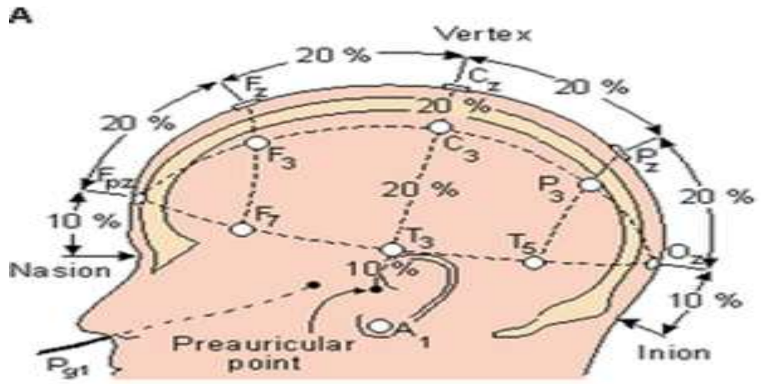

Fig1.3.1 10-20 international system

IV. EEG WAVE-GROUP

The analysis of continuous EEG signals or brain waves is complex, due to the Large amount of information received from every electrode. As a science in itself, it has to be completed with its own set of perplexing nomenclature. Different waves, like so many radio stations, are categorized by the frequency of their emanations and, in some cases, by the shape of their waveforms. Although none of these waves is ever emitted alone, the state of consciousness of the individuals may make one frequency range more pronounced than others. Five types are particularly important:

BETA: The rate of change lies between 13 and 30 Hz, and usually has a low voltage between 5-30 μV Beta is the brain wave usually associated with active thinking, active attention, focus on the outside world or solving concrete problems. It can reach frequencies near 50 hertz during intense mental activity.

ALPHA: The rate of change lies between 8 and 13 Hz, with 30-50 μV amplitude . Alpha waves have been thought to indicate both a relaxed awareness and also inattention. They are strongest over the occipital (back of the head) cortex and also over frontal cortex. Alpha is the most prominent wave in the whole realm of brain activity and possibly covers a greater range than has been previously thought of. It is frequent to see a peak in the beta range as high as 20 Hz, which has the characteristics of an alpha state rather than a beta, and the setting in which such a response appears also leads to the same conclusion. Alpha alone seems to indicate an empty mind rather than a relaxed one, a mindless state rather than a passive one, and can be reduced or eliminated by opening the eyes, by hearing unfamiliar sounds, or by anxiety or mental concentration.

THETA: Theta waves lie within the range of 4 to 7 Hz, with an amplitude usually greater than 20 μ V. Theta arises from emotional stress, especially frustration or disappointment. Theta has been also associated with access to unconscious material, creative inspiration and deep meditation. The large dominant peak of the theta waves is around 7 Hz.

DELTA: Delta waves lie within the range of 0.5 to 4 Hz, with variable amplitude. Delta waves are primarily associated with deep sleep, and in the waking state, were thought to 15 indicate physical defects in the brain. It is very easy to confuse artifact signals caused by the large muscles of the neck and jaw with the genuine delta responses. This is because the muscles are near the surface of the skin and produce large signals whereas the signal which is of interest originates deep in the brain and is severely attenuated in passing through the skull.

V.FEATURE EXTRACTION

Various tools are available for feature extraction for example wavelet, short Fourier transform, and Fast Fourier transform. In this research we use FFT to extract the feature. The FFT (Fast Fourier Transform) is a mathematical process which is used in EEG analysis to investigate the composition of an EEG signal. Since the FFT transforms a signal from the time domain into the frequency domain, frequency distributions of the EEG can be observed.

$$X(f) = \sum_{n=0}^{1024} e^{-2j\Pi nf}$$

We cut 2 second epoch from recorded EEG signal and take 1024 point FFT at 256 Hz sampling rate and then find power spectral density for various frequency band. EEG signal x(t) has Fourier transform x(f),its power spectral density is │x(f)│^2=s(f)

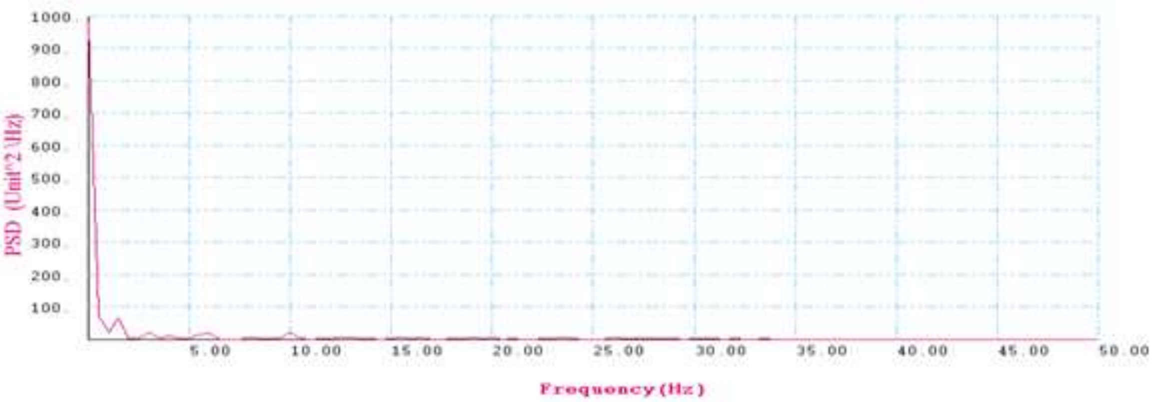

Fig 5.1: PSD of f3 electrode of alcoholic person (2 sec epochs)

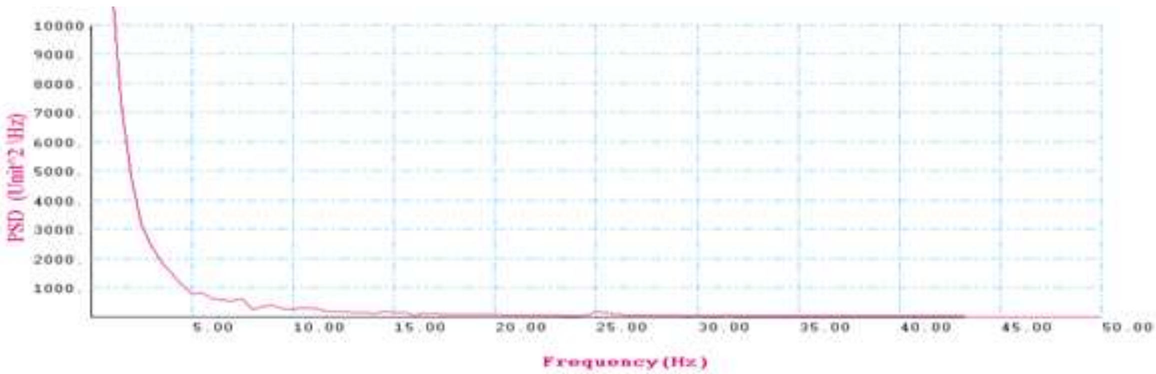

Fig5.2: PSD of f3 electrode of control subject (2 sec epochs)

Four feature is extracted from recorded EEG signal .Feature is absolute power, relative power, peak power frequency and mean power frequency.

Absolute spectral power in the band of frequencies from f0 Hz to f1 Hz is the total power in that band of frequencies, that is, the total power delivered at the output.

absolute spectral power in band $=\sum_{n=1}^{205} s_x$ (f)

Relative power is the ratio of total power in band and total power in signal.

Relative power = [$\sum_{n=1}^{205} s_x\ (f) \div \sum_{n=1}^{1024} s_x$ (f)]*100

Peak power frequency (PPF) is the frequency where peak power is obtained in given frequency band (delta, theta, alpha, beta1, beta2).

Mean power frequency (MPF) is the frequency where average power is obtained. Finally we get 200*5 data matrix from each electrode

VI.FUNCTIONAL LINK ARTIFICIAL NEURAL NETWORK

The FLANN was first purposed by Pao [4] is a single layered artificial neural network structure capable of performing complex decision region by generating non-linear decision boundary. The FLANN can be used for function approximation and pattern classification with faster convergence and lesser computational complexity than a MLP network. In Functional Link Artificial Neural Networks (FLANNs), the hidden layer is removed without giving up non-linearity by providing the input layer with expanded inputs that are constructed as the functions of original attributes Removal of hidden layer makes these networks extremely simple and computationally cheap The architecture becomes simple and training does not involve fullback propagation. Thus, nonlinear modelling can be accomplished, by means of a linear learning rule, such as delta rule.

6.1: Different types of functional expansion

$X=[x_1, \cos(\pi x_1), \sin(\pi x_1), \cos(2\pi x_1), \sin(2\pi x_1)\ldots x_2, \cos(\pi x_2), \sin(\pi x_2), \cos(2\pi x_2), \sin(2\pi x_2)\ldots x_1x_2]^T$

Using exponentional and power series expansion the enhancement will be

$X=[x_1, \exp(x_1), \exp(2x_1)\ldots. x_2, \exp(x_2), \exp(2x_2)\ldots.]^T$

$X=[x_1, x_1^2, x_1^2, \ldots\ldots x_2, x_2^2, x_2^2, \ldots. x_9, x_9^2, x_9^2]^T$

The exponential polynomial expansion needs less number of computations and is very easy to implement then other three type of polynomial expansion. Power series polynomial expansion is more difficult to implement then other three type of polynomial expansion in real time processing [5].

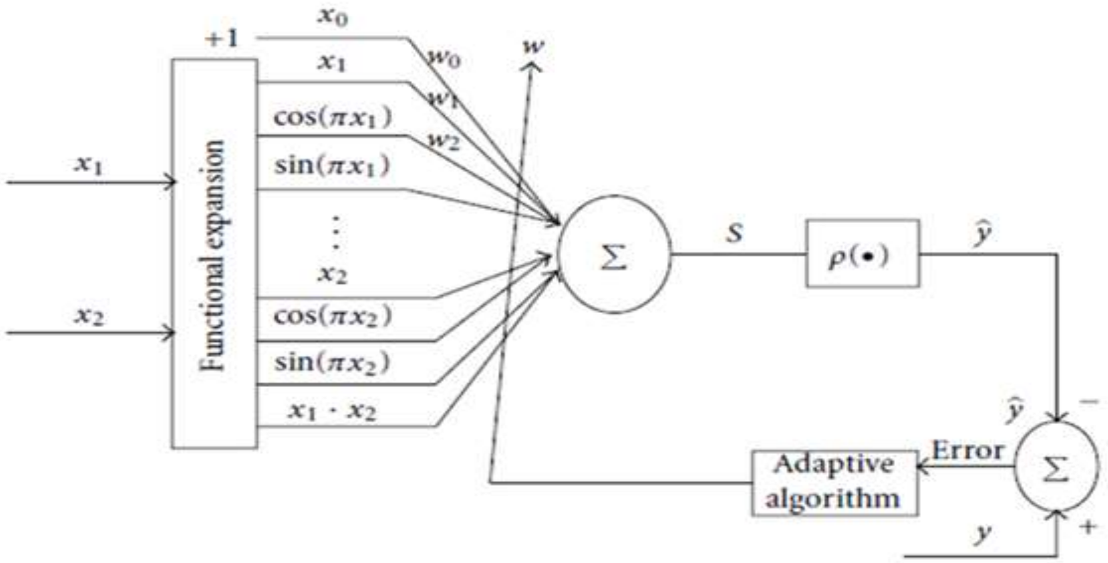

Fig.6.1 FLAN Structure

In FLANN we use five inputs and expand every input into five dimensions so for five inputs we get twenty five (expanded input). This expanded input is multiplied with weight and take summation.

In this FLANN we use signum function as an activation function. Applying this activation function we get output and this output is compared to desired output we get an error this error is used to optimised the weight by use of adaptive algorithm. In adaptive algorithm we use least mean square (LMS) algorithm to update the weight that is W (n+1) =w (n) +ηx (n) e (n), Where η = learning rate

X = input vector, e = error, Output, y (n) = w^{h}x(n), Error, e (n) = d*(n) – y(n)

6.2. Convergence and Stability of the LMS algorithm

The LMS algorithm initiated with some arbitrary value for the weight vector is seen to converge and stay stable for 0 < μ < 1/λ max Where λmax is the largest eigenvalue of the correlation matrix R. The convergence of the algorithm is inversely proportional to the eigenvalue spread of the correlation matrix R. When the eigenvalues of R are widespread, convergence may be slow. The eigenvalue spread of the correlation matrix is estimated by computing the ratio of the largest eigenvalue to the smallest eigenvalue of the matrix. If μ is chosen to be very small then the algorithm converges very slowly. A large value of μ may lead to a faster convergence but may be less stable around the minimum value. One of the literatures [will provide reference number here] also provides an upper bound for μ based on several approximations as μ <= 1/(3trace(R)).

We trained the network (90% training data) for 1000 times at learning rate 0.003 we get updated weight vector is W=[3.145, 0.4050, -0.5459, 0.4114, -0.0422, -0.3012, -0.111, -0.3563, 0.3379, 0.0991, 0.3690, 0.3560, 0.3118, -0.1409, 0.3057, -0.3045,0.0017,0.1477,0.3592,0.1577,0.2543,-0.3781,-0.0484,0.3236,-0.1439]

Now this updated weight vector is used to test data(10% testing data) then we get result.

Y=sign(sum(w.*x(n)))

VII.RESULT

By using support vector machine as classifier then we get most prominent electrode is F3 and frequency band is peak power frequency to classify alcoholic and non-alcoholic person. By using FLANN (functional link artificial neural network) most prominent electrode is also F3 to classify alcoholic and non-alcoholic.

By the use of SVM

electrode	delta	theta	alpha	beta1	beta2
C3	52	62	62	75	63
C4	51	57	50	55	47
Cz	48	65	53	68	76
F3	56	67	50	68	70
F4	52	63	56	77	71
Fz	53	63	52	50	46
P3	55	63	60	67	66
P4	48	65	57	67	62
pz	51	61	62	35	58

Accuracy in feature ABSOLUTE POWER

electrode	delta	theta	alpha	beta1	beta2
C3	68	58	66	53	70
C4	62	62	62	50	50
Cz	67	56	56	46	57
F3	43	77	77	60	60
F4	68	63	63	46	62
Fz	58	67	67	65	65
P3	67	55	55	52	57
P4	58	67	67	48	56
pz	65	65	65	67	62

Accuracy in feature RELATIVE POWER

electrode	delta	theta	alpha	beta1	beta2
C3	55	62	68	43	58

electro de	de lta	th eta	alp ha	be ta1	be ta2
C3	60	67	71	47	55

C4	53	60	63	58	61
Cz	61	63	63	52	63
F3	57	80	60	55	47
F4	50	67	68	52	57
Fz	62	65	65	55	60
P3	58	53	61	47	60
P4	46	62	66	63	63
pz	53	73	71	56	46

Accuracy in feature PPF (peak power frequency)

C4	53	63	56	56	53
Cz	58	62	61	52	58
F3	63	58	56	50	51
F4	53	57	58	53	58
Fz	63	61	58	57	53
P3	56	56	66	47	62
P4	56	60	63	66	55
pz	57	71	73	55	55

Accuracy in feature MPF (mean power frequency)

By use of FLANN

ELECTRODE	ALCOHOLIC (%)	CONTROL(%)
C3	50	35
C4	60	45
CZ	30	55
F3	50	55
F4	30	40
FZ	55	50
P3	35	45
P4	50	35
PZ	48	65

accuracy in ABSOLUTE POWER

ELECTRODE	ALCOHOLIC (%)	CONTROL(%)
C3	60	25
C4	70	10
CZ	75	10
F3	80	79
F4	75	0
FZ	75	10
P3	60	8
P4	70	8
PZ	60	0

Accuracy in PPF(peak power frequency)

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