Artifact Removal and of EEG Signal Classification for Brain Computer Interface (BCI) using Back Propagation

Rajashekhar U., Neelappa, Rajesh

***Abstract:** A brain-computer interface (BCI) provides a communication passage between the brain and an external stratagem. The Brain and its EEG signals are acquired from the BCI along its control signals and its widely used mechanism in the field of the biomedical fields. In this research work, an artifacts are removed algorithm in the EEG is developed and simulated in the MATLAB 2017a software tool. EEG signals from patients are recoded while recording some of the artificial signals added to it, which are instigated by using eye blinks, eye movement, muscle, and cardiac noise, and also non-biological sources. Using suitable filters these artificial signals can be removed. This paper aims to remove the artificial signals from EEG signals and parameters like mean, standard. Deviation are calculated and compared with other methods such as LAMICA and FASTERs. In the paper, it is also the proposed arrangement of EEG signals for the discovery of typical and anomalous exercises utilizing Wavelet change and Artificial Neural Network (ANN) Classifier is considered. Here, the framework utilizes the back proliferation with feed-forward for order which pursues the ANN grouping. Accuracy of the classification is calculated and compared with other states of art publications and found that it is better.*

***Keywords:** Electroencephalogram (EEG), Brain-Computer Interface (BCI), Artifacts, Independent Component Analysis (ICA), Blind signal separation (BSS).*

I. INTRODUCTION

Brain computer interface (BCI), is a framework that empowers people to collaborate with their surroundings by means of utilizing control signals created from electroencephalographic (EEG) movement, without the intercession of fringe nerves and muscles and it is an immediate correspondence pathway between a human brain and an outside device[1]. Such frameworks enable individuals to convey through direct estimations of mind action, without requiring any development [2]. BCI has many applications in research networks neuroscience, neuroimaging, recovery drug, design acknowledgment, signal preparing, AI, etc. One of the objective of BCI investigate is to reestablish standard capacities for individuals with extreme neuromuscular inabilities sign pathway.

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Rajashekhar U., Research Scholar, Department of Electronics & Communication Engineering, Government Engineering College, Kushalnagar, Karnataka and affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India. E-mail: uraju54@gmail.com

Neelappa, Department of Electronics & Communication Engineering, Government Engineering College, Kushalnagar and affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India. E-mail: neel.m.dy@gmail.com

Rajesh, Department of Electronics & Communication Engineering, East Point college of Engineering and Technology Bengalore, Karnataka, India.

Seemingly, the most generally utilized instrument for procuring MCI control signals from the mind is the electroencephalogram (EEG). The EEG is generally utilized in clinical practice as a result of its minimal effort and its absence of symptoms because of its noninvasive nature [3]. The EEG records added electrophysiological movement created from cortical neuronal action and anticipated through the skull and scalp [6].

II. RELATED WORK

This segment addresses the issue of expansion of a counterfeit sign. Specifically for BCI depends on electroencephalogram (EEG), where electric possibilities recorded from anodes set on the scalp give direct proportion of cerebrum action. Be that as it may, EEG accounts are typically polluted by undesired signal called relics and they are brought about by endogenous (e.g., physiological sources, for example, eye, muscle and cardiovascular action) and exogenous (e.g., non-physiological sources, for example, impedance befuddle, control line coupling, and so forth.) reasons [4]. There is a need to expel every one of these relic types preceding examination of the EEG and its utilization in BCI control, to guarantee that any control accomplished might be truly credited to the member's cerebrum action. Be that as it may, this is a non-unimportant undertaking. Ancient rarities, especially member created curios, possess over lapping phantom groups with the neurological action of intrigue, may happen on numerous or all channels, and frequently have bigger sufficiency than the EEG signal parts of intrigue. Hence, basic recurrence band or spatial sifting won't satisfactorily expel them [4]. Since Hans Berger detailed the main procurement of human EEG in 1929 unique strategies have been utilized to deal with EEG ancient rarities. These incorporate three unique gatherings of strategies, in particular I) antique shirking (e.g., advising subjects to abstain from moving or squinting during the investigation and look at a focal obsession point), ii) ancient rarity dismissal (e.g., disposing of defiled preliminaries by visual review or via programmed methodology), and iii) curio expulsion dependent on pre-handling of the EEG information [2]. Many authors are worked on EEG and BCI and complete related literature review is presented in the table 2. 1 and table 2.2.

A wide range of computerized antiquity expulsion techniques have been proposed for EEG de-noising. Wavelet-based de-noising is utilized for the evacuation of antiquities while transmitting the EEG signals. The total writing survey is introduced in the 2.1. What's more, table 2.2. The rest of the paper is organized as follows, Section I contain the Introduction about BCI and its applications, Section II related work, Section III contain the study area and the methodology proposed, Section IV contain Result Analysis. In section V describes the conclusion.

III. PROPOSED METHODOLOGY

In the proposed methodology there are three basic stages, they are input data, Pre-processing, feature extraction and artefacts removal. In input data stage data is collected from patients through online i.e., EEG signals of a patient. This raw EEG data is usually not clean for further processing therefore preprocessing is required. The preprocessing is usually a high-pass channel to evacuate the DC segments of the sign and furthermore the floats (normally a recurrence cut-off of 1 Hz is sufficient). A low pass channel can likewise be applied to evacuate the high recurrence segments. In EEG flag presently once in a while study frequencies over 90 Hz which compare to the Gamma extend. When sign are preprocessed, it is very basic to cut them in ages of a couple of moments and afterward in second stage separate highlights out of every single one of these. Then noises are removed in the Artifacts removal stage. Cleaned EEG signals are obtained at the output. The flow diagram is represented in the figure 3.1

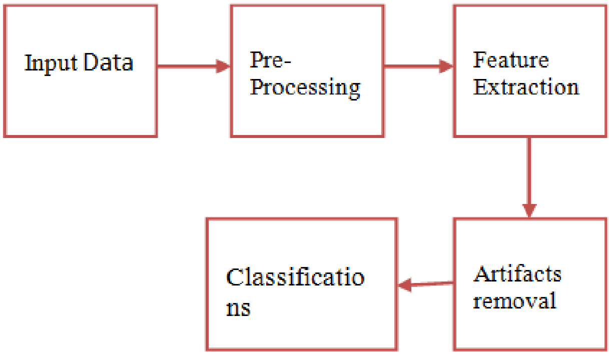

Figure 3.1 Proposed Methodology for BCI

TABLE 2.1 LITERATURE REVIEW

Ref no.	Method	Result
[04]	In view of sensorimotor musicality regulation and unfaltering state visual evoked potential.	Providing better BCIs method to control needs of individuals with CP.
[05]	BSS/ICA method	Utilizing channels that expel the relics from BCI information.
[07]	Unsupervised method	Evaluate the utility and execution of FASTER.
[08]	Wavelets BSS and MSSA	Three techniques are presented for mechanized relic adjustment in the EEG.
[09]	Statistical method	Ancient rarities of EEG are expelled with the assistance of wavelet deterioration.
[10]	Electrocardiogram data Compression	PRD,SNR,QS,PRDN & RMS are better
[14]	P300 classification methods	Improve the general unwavering quality of BCI framewo
[15]	Second-order blind identification (SOBI)	Improves the SNR and decrease the degree of subjectivity
[16]	Independent component analysis(ICA)	Distinguishing and disposing of EMG Contamination.
[17]	Innovative methodology	Mechanical antique from musical stride occasions limited utilizing layout relapse strategy.
[18]	Signal acquisition	EEG signals are compacted utilizing DWT based partner for good remaking quality.

TABLE 2.2 LITERATURE REVIEW

Reference	Dataset	Method	Accuracy
[21]	64 and 32 electrodes cap, 8 channels.	ICA,MNE or PCA	85%
[22]	32-electrods cap, 8 channels.	SVM	91.26%
[23]	32-electrods cap, 8 channels.	SVM	80%
[24]	32-electrods cap, 8 channels.	SVM	91%
[25]	16 electrodes cap, 16 channels	Spatial-Temporal Discriminant Analysis(STDA).	80.8%
[26]	64 electrodes	SVM	84.5%
[27]	60,118 and 32 channels	CSP	95%
[28]	59 and 22 channels.	CSP	--
[29]	105 and 120 channels, 27 and 57 electrodes.	SVM	98.9%

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[30]	6 channels and 26 electrodes	LVQ and MLP	70%
[31]	30 channels and 10 to 20 electrodes	CCA,MCCA and L1-MCCA	80%
[32]	9 electrodes	SVM and variation RVM	80.68%
[33]	64 electrodes and 30 channels	Group Sparse Bayesian Linear Discriminant Analysis. (GSBLDA)	90%

IV. RESULTS AND DISCUSSSION

Various sorts of strategies have been created in two significant zones like spatial space and recurrence area for the decrease of dot commotion. In the present work, the fundamental fixation is on some significant zones of de-dotting strategies. Primarily the de-spotting techniques are extensively given as Kaun Wavelet change, Principal Component-based change, Non-Local Mean strategy, Probabilistic Patch Based technique, and so on. All standard spot channels utilize neighboring pixels measurable attributes inside the nearby window to figure the normal worth expected to supplant the separated pixel. The size of the channel window will decide the measure of dot diminished and the visual nature of the denoised picture. So by a mix of wavelets and thresholding ancient rarities are evacuated.

4.1 Simulated Results for Artifacts Removal

The results of the proposed work are presented in the following sections. The results includes, the results of preprocessing, feature extraction and artifacts removal. Performances of the proposed work are compared with the state of art work.

a. *Input data set:*

The input data is EEG signal which is collected from the online shown in Figure 4.1. X-axis having sample index and Y-axis having amplitude. Collected EEG signal are contaminated by noises called as artifacts.

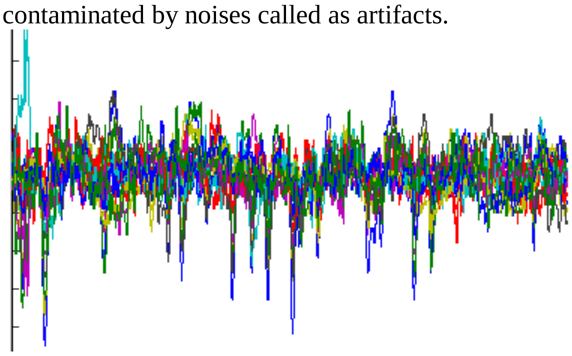

Fig 4.1. Input EEG signal of a patient

b. Separation of Brain Waves:

Figure 4.2.. shows the brain wave separated from the input EEG signal. There are various Brain waves present in an EEG signal like gamma, beta, alpha, theta and delta. These brain waves contribute to the various state of mind. Those waves consist of noises those are filtered by a suitable filter. Filters are filter out the noise signal. Classification of these waves and removing the noise signal are comes under pre-processing stage. The EEG in each region is filtered into the gamma, beta, alpha (8–12Hz) theta and delta (13–35 Hz) frequency bands.

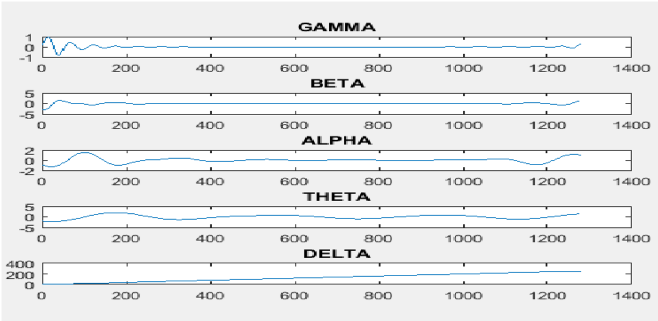

Figure.4.2. Filtered input data set

4.2 Artifacts Removal

Figure 4.3. shows the recorded EEG at 512 Hz and it consist of 16 channels. After the selection of input EEG signal desired method i.e., Discrete Wavelet Transform (DWT) is helps to separate the noises in an EEG signal. Decomposed using a Discrete Wavelet Transformation (DWT) and thresholding. In wavelet decomposition, wavelets attempt to decompose a signal. The daubechies ‘db20’ mother wavelet is used in this work to decompose the signals into approximation and detail coefficients down to 2 decomposition levels. The basic idea of wavelet technique is that noise mainly exists on the high frequency components and thus can be removed. DWT is a discrete form of ceaseless wavelet change and its calculation may expend huge measure of time and assets, contingent upon the goals required. The DWT depends on sub-band coding, is found to yield a quick calculation of wavelet change. It is simple for usage and lessens the calculation time and assets required.

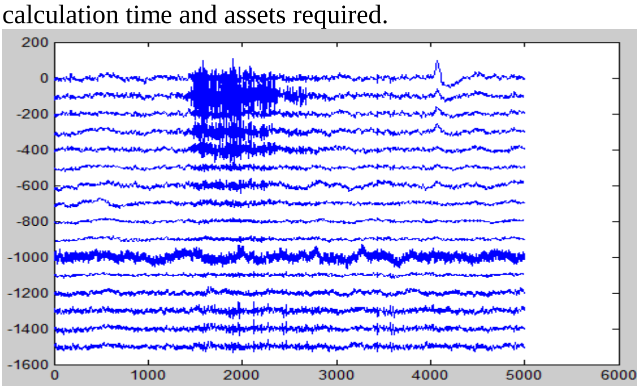

Figure 4.3. Recorded EEG

a. *Cleaned EEG Signal:*

Figure 4.4. shows the cleaned EEG signal x-axis represent a time in second and y-axis represent a channels. It mainly works based upon the combination of wavelet decomposition and thresholding.

The following steps followed to remove the artifact
Step1: Decompose the EEG on each channel into a set of approximation and detail coefficients via wavelet decomposition.
Step2: Identify spikes zones in both approximation and detail coefficients sets
Step3: Then apply the soft thresholding.
Step4: Remove the artifacts.

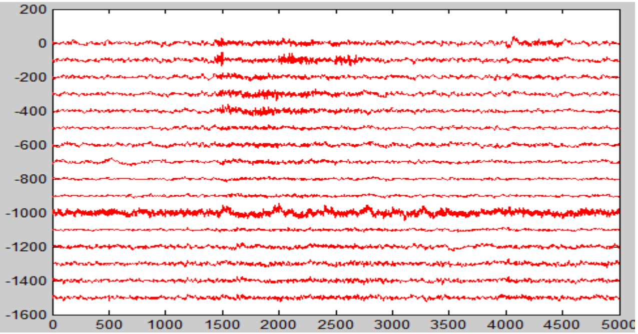

Figure 4.4. Cleaned EEG signal

Artifacts are known to differ from clean EEG in the following properties

1. The amount of temporal dependency within the signal.
2. The amount of spiking activity.
3. Measuring the peaked ness of the signal amplitudes over times.
4. The power spectral density in the gamma frequency band and above (>30Hz)
5. The peak amplitudes of the EEG time series.

b. Power Spectral Density (PSD):

Figure 4.5. shows the power unearthly thickness of EEG sign and Fig.6. shows its chart. The PSD is determined by Fourier changing the evaluated autocorrelation succession which is found by nonparametric strategies. One of these techniques is Welch's strategy. The information succession is applied to information windowing, creating adjusted periodograms [19]. The data grouping x_i (n)is communicated as

$x_i(n) = x(n + iD)$ n=0,1,2.….M-1
While i=0,1,2.….L-1

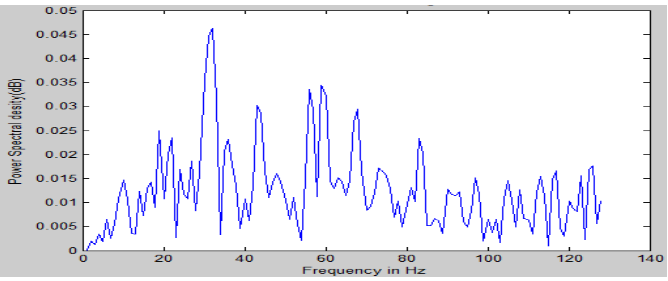

Figure 4.5 Power spectral density

c. Comparison Between Different Methods

The proposed method is compared against the Fully automated statistical thresholding (FASTER) and Lagged auto-mutual information clustering (LAMIC) method are presented in the table 4.4 and table 4.5 and also in the Fig.7 and Fig.8

TABLE 4.4: Mean SQI calculated from original EEG signal

Method	Mean	Std.
Original EEG	0.133	0.032
LAMIC	0.099	0.039
FASTER	0.091	0.030
FORCe	0.063	0.024
Proposed method	0.055	0.015

TABLE 4.5 Mean and STD.ERD\S calculation

Method	Mean	Std.
Original EEG	0.316	0.171
LAMIC	0.331	0.224
FASTER	0.322	0.179
FORCe	0.359	0.155
Proposed method	0.340	0.145

Fig.7. Mean and STD.ERD\S calculation

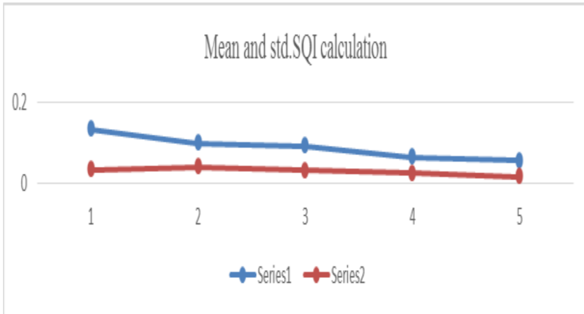

Fig.8.Mean and std. SQI calculation

From the figures and tables is very that, proposed method has better results than other methods such as Lamic, Faster and Forces methods.

4.2 Simulation results and Analysis of Classification of EEG signal:

In this section, the simulated results of each stage are presented and discussed

a. Diseases classification:

In this stage classifying the collected EEG signal either normal or abnormal. In abnormal stage classifying the two diseases Epilepsy and tumor.Step1: After data collection, before parameter extraction is being done, a set of measurements is to be performed. The signals are acquired using the electrode placement or EEG signal can be collected from Physio Bank in www.physionet.org website. The Figure.4.5. shows the original input signal.

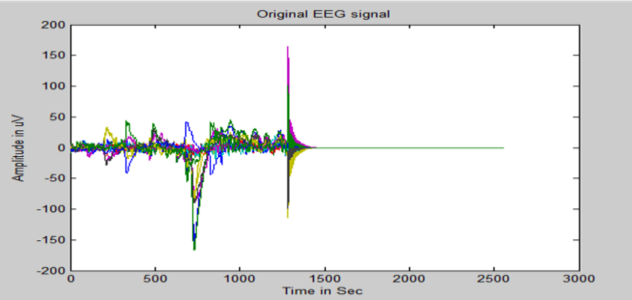

Fig.ure 4.5. Input of EEG signal

Step2: . Pre-preparing procedures help to expel undesirable ancient rarities from the EEG flag and henceforth improve the sign to clamor proportion. A pre-handling square guides in improving the presentation of the framework by isolating the clamor from the real sign. In proposed strategy utilizing recursive least squares (RLS) is a versatile channel that recursively finds the coefficients that limit a weighted direct least squares cost work identifying with the information signals. Normalizing the all the co-efficient and finding the mean to minimizing the error. The preprocessed signal which is free from noise signal is shown in Fig.10.

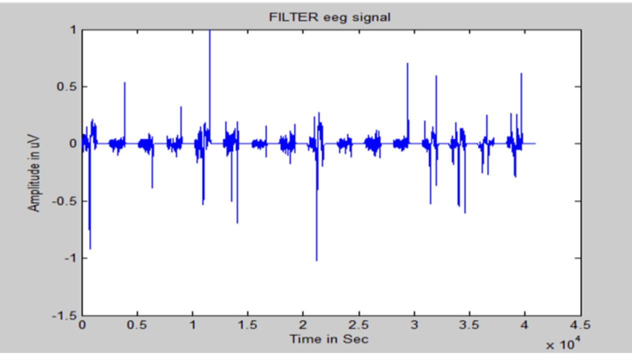

Fig.re 4.6. Filtered of EEG signal

Step 3: In the element extraction stage, the data that is generally significant for arrangement is extricated from the crude information. The EEG signal is an unpredictable capacity of the cerebrum attributes, for example, mental pressure, passionate state, neurological issue, e.g., epilepsy, early determination and restriction of mind tumors. In the proposed paper Discrete Wavelet Transform is utilized. Wavelets are valuable in light of the fact that as they evacuate the most elevated frequencies, nearby data is held and the picture resembles a low goals variant of the full pictures. The feature extracted signal is shown in Figure.4.7

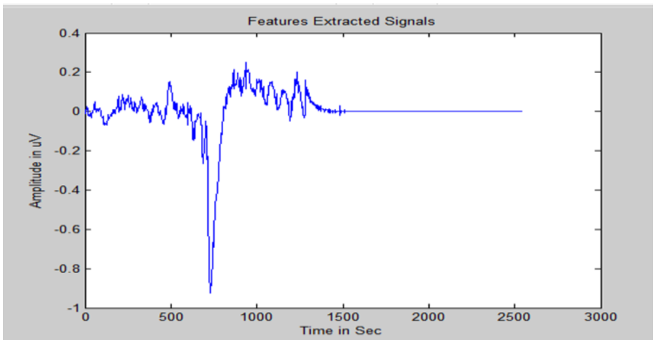

Figure 4.7: Feature extracted of EEG signal

Step 4: The activity of the grouping step is rearranged just like that of changing quantitative info information to subjective yield data. ANNs can be prepared to recognize non-straight examples among info and yield esteems and can take care of issues a lot quicker than advanced PCs, a feed forward neural system prepared utilizing Back proliferation is utilized for the acknowledgment of epileptic examples in EEG signals. The ANN EEG signal is shown in fig 4 and the complete noise is removed based on the ANN & BP signal as shown in Figure4.8.

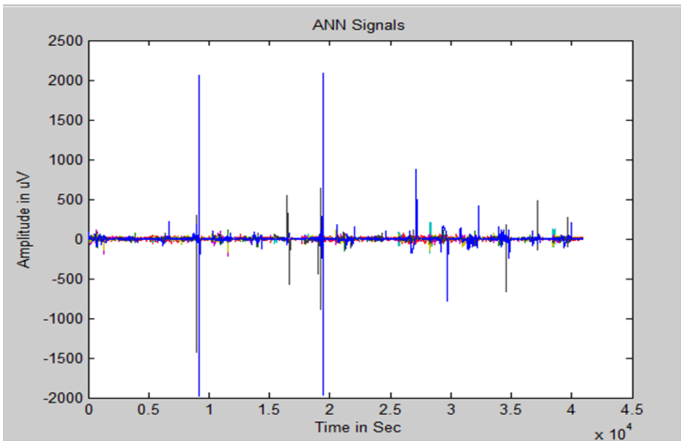

Figure 4.8: ANN of EEG signal

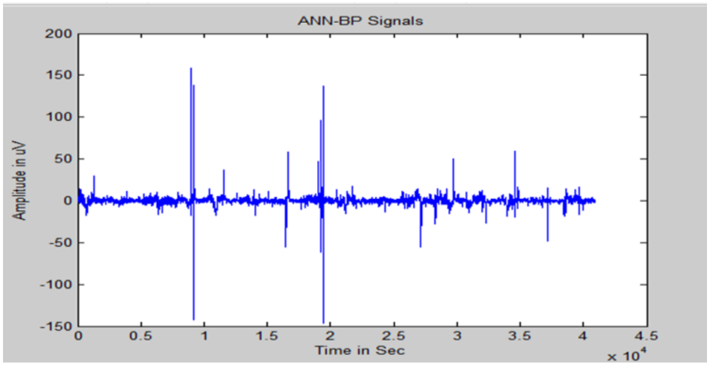

Figure.4.9. ANN-BP of EEG signal

Different brain signal has been tested, signal represented performance can be validated as shown in the Figure.4.9. and the complete performance steps has shown in GUI Fig.

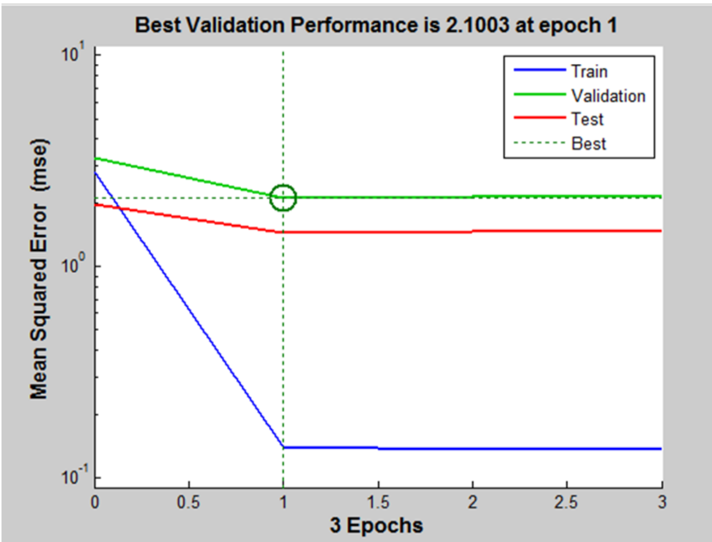

Figure.4.10. Best validation performance of EEG signal

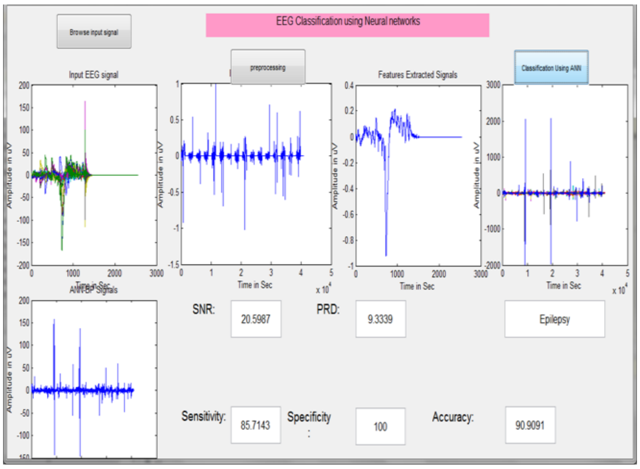

Fig.ure 4.11. GUI Representation of EEG signal

The second and third examples are also taken and steps are carried out as in the first example. The performance of comparison in terms of various parameter are presented in the table 4.1.The performance is also presented graphically in Figure.4.11.

Table 4.1: Performance comparison

Diseases case	SNR (db)	PRD	Sensitivity(%)	Specificity(%)	Accuracy	MSE
NORMAL	27.7172	4.1128	85.7	100	90.9	1.8249
EPILIPSY	20.59	9.33	85.5	100	90.5	2.100
TUMOR	19.8294	10.1984	84.9	100	91.1	2.25

The statistical parameters of the SVM and MLPBP are compared in table 4b.2 and in figure 4.9 and figure 4.10 From the tables and figures it is found that, the performance of the MLPBP is better than SVM.

Table 4.2: The Statistical Parameters Comparison of the SVM and MLPBP Classifiers

Sensitivity (%)	Specificity (%)	Accuracy %
93.25	96.44	93.63
93.63	95.36	93.63
94	94.16	93.63
94.13	97.17	93.63
93.13	99.5	93.63

Sensitivity (%)	Specificity (%)	Accuracy %
99.25	99.84	99.28
99.38	98.44	99.28
99.25	99.75	99.28
99.38	99.65	99.28
99.18	100	99.28

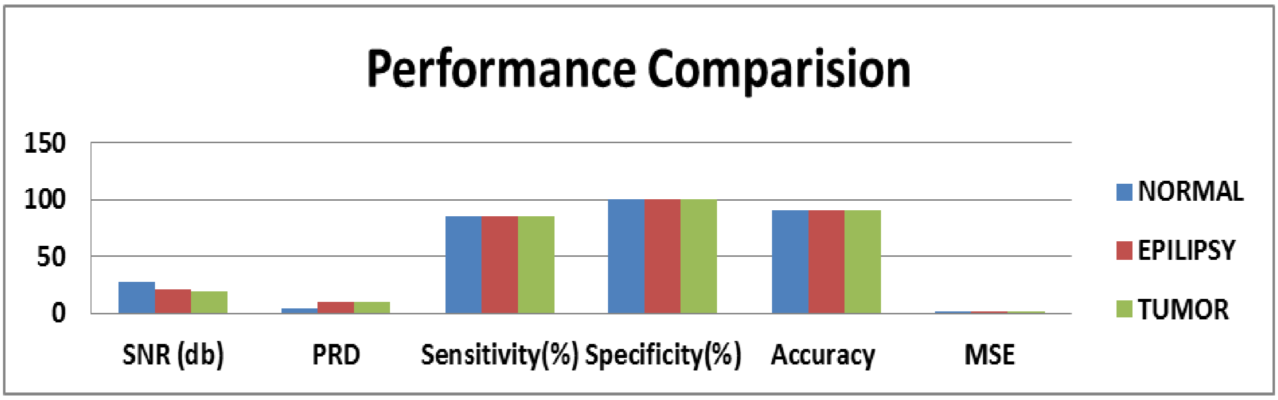

Figure 4.9: Performance comparison

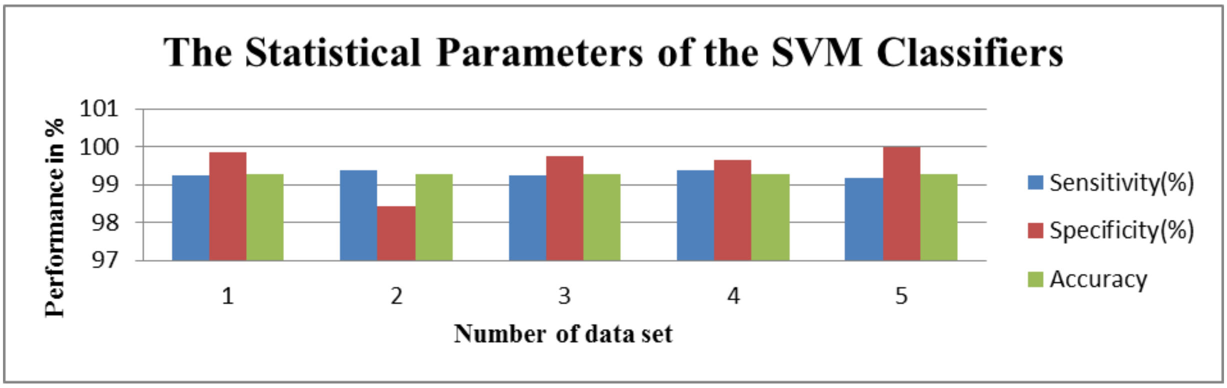

Figure 4.9: The Statistical Parameters of the SVM Classifiers

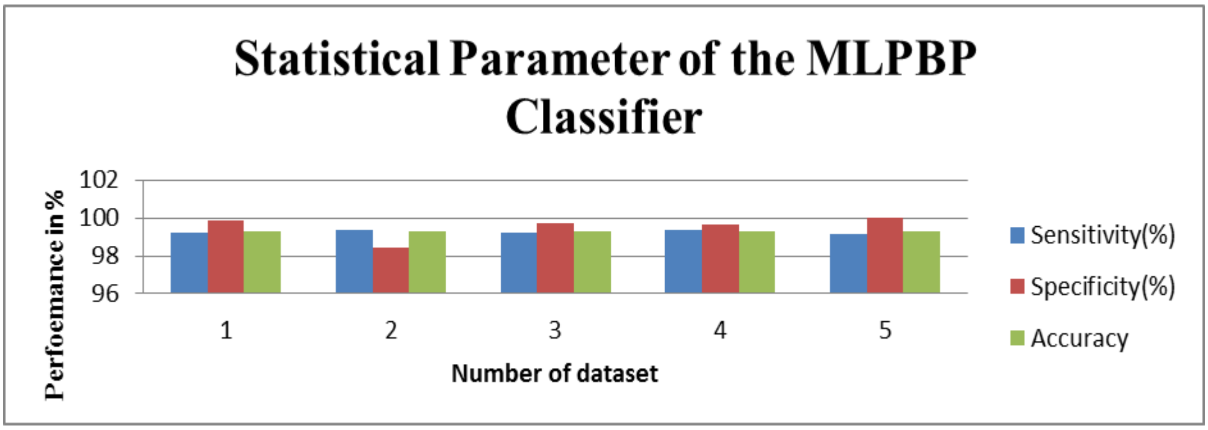

Figure.10: The Statistical Parameters of the MLPBP Classifiers

V. CONCLUSION

In the paper the EEG signal is from database is taken is preprocessed then content of artifact is removed and it is classified. The parameters such as power spectral density, mean and SQI are calculated. The percentage of accuracy found out for the different signals which are having different diseases such as tumor and epilepsy. Some of the parameters are calculated for the different signals such as SNR, PRD, Sensitivity, Specificity and accuracy. The percentage of accuracy is compared with SVM classifier and it is found accuracy better than SVM classifier.

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