# Epilepsy Seizure Prediction Model Based on Dual Mode EEG Overlapping Technique Using Neural Network

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***Abstract*—Epilepsy Seizure is a neural malfunction of electrical ions discharging or ex- changing among the neurons. Typically, the cause and purpose of occurrence is untraced as the normal ions charge based communication is uninterruptable. Various researchers have proposed techniques to analyses the seizure occurrence using Electro Encephalogram (EEG). In this paper, a dual mode EEG overlapping algorithm is proposed towards the detection of Epilepsy Seizure (ES) occurrence under an asymptomatic patient's datasets. The approach trains datasets under normal and abnormal conservative scenarios. The slightest change of fluxes in ions leads to the blank edge formation i.e., Epilepsy Seizure. The process is then evaluated under a neural networking model. The EEG datasets are formulated with a synchronized pattern leading towards authentication of change. The algorithm is validated on 345 clinical samples approved by medical research communities. The algorithm demonstrates the higher order of Epilepsy Seizure prediction and detection. The sample based validated results is 97.32% accuracy rate in detection with a non-fatal ratio of 2.68% of true negative predications.**

## I. Introduction

An advance in biomedical signal processing is a boon of modern technological enhancements and influence of research in embedding technology with medicine. In this article, a systematic evaluation of Epilepsy Seizure (ES) is discussed. Epilepsy Seizure is a neural disorder of ion distortion and a malfunction of flex balancing in-terms of charges involved in communicating across the neuron. The process of Epilepsy Seizure is relatively last for a minimal duration and henceforth, the occurrence pattern and reason of origin is primarily under explored from medical community. The Epilepsy Seizure is classified as chronic dis- order, involving in producing a mass of electric flexes (instructions) to the brain. Epilepsy Seizure based diagnostic challenges are discussed by [1] (Elger C E et. al 2018) with a detailed overview processing based on the internal observations and types of seizure involved. The authors have also discussed clinical trial evaluation challenges and tonic-clonic seizures generalization and evaluation schema. The tonic-clonic seizure's generalization can be visible and is classified with a limb and truck muscle expansions and the most common of the symptoms and signs of patients suffering from Epilepsy Seizure. Epilepsy Seizure is broadly analyzed and pro- cessed using EEG signals retrieved from the electrodes and drafted brain activates. Certain set of authors have also concentrated on non-EEG based evaluation approaches (Van de vel et.al 2016) [2] towards development and prediction using technological improvement of smart-phones lead- ing towards building new standards of Epilepsy Seizure evaluation. The research also extends rel- ative dependencies on data monitoring and data origin. The proposed technique aims to cite a sensible reference in predicting the occurrence pat- tern of Epilepsy Seizure using EEG datasets un- der textural format. The article is discusses a literature survey in section 2 followed by problem state and the proposed technique in section 3 and 4 respectively. The results and discussion section is cites, outcomes and evaluation of clinical trial in 5 and followed by conclusion in section 6.

## II. Literature survey

Epilepsy Seizure diagnosis, prediction and oc- currence ratio is under research since the early days of trivial research. With the enhancement of science and technology, research methodologies are enhanced and gapped to provide higher or- der of results and virtual clinical evaluations and trails, due to clinical evaluation and prediction of dependable results, it is recommended to undergo the evaluation process using EEG or Video EEG signal processing. In [3] (Hassan A R. et.al 2020) has proposed CEEMDAM, signal processing technique to optimize the noise ratio using empirical mode decomposition and hence a scalable diagnosis system is proposed and validated with a similar pattern of nonlinear classifier as proposed by (Martinez-del-Rincon J, et. al 2017) [4] the non-linear SVM and Bag of Words (BoW) approach has improved accuracy rate of detection. The approach has produced 10% higher accuracy compared to previous approaches.

According to the study, Epilepsy Seizure is affected by 1% of world population by (Shoeb A, et.al 2004) [5] also evaluated the seizure occur- rence and time of activation. Though ES is a com- mon disease, the medical instruments and tools for diagnosis are under-production and thus re- sulting in a mass of research gaps. EEG based evaluation requires an electrode-based signal remitter and thus causing a lapse in infrastructural enhancements. As mentioned, the technological

improvements have enhanced the prospective of evaluating ES. The use of deep learning-based approach (Hossain M S, et.al 2019) [6] has proposed Deep Convolutional Neural Network (CNN) in extracting robotic features of EEG datasets and recorded a 99.64% of accuracy of patient specific data. Thus, the implementation based on CNN has opened new dimensions in viewing EEG datasets. To support probability-based technique, (Kuhlmann L, et.al 2009) [7] has discussed a statically evaluation of ES with feature compression leading towards seizure detection.

In the latest development, an automatic evaluation technique using wavelets and Artificial Neural Network (ANN) is proposed (Vani S, et.al 2019) [8], the technique claims to be evaluated under HAAR based wavelet decompositions on a multi-channel EEG dataset. The improvisation needs to be recorded in designing and develop- ing an infrastructure based on the study of ob- servation. A recording is made on EEG dataset processing only on an abnormal dataset i.e., certified datasets with ES positive under clinical trials. Thus, a lack of observative study with respect to asymptomatic patients is yet to be considered and evaluated. Henceforth, proposed technique bridges the gaps in understanding and evaluating ES prediction and occurrence pattern with respective to dual mode overlapping technique using neural networks.

## III. PROBLEM STATEMENT

Epilepsy Seizure is a classified neural disorder with an improper ratio of occurrence and under- standings. The process of seizure is acute and last on maximum of five to seven minutes and hence the pattern computation ratio is estimated to be 28.7% from latest research findings, the challenging scenario is highlighted while prediction is inaccurately paired with normalized EEG signals. Thus, a research gap is to identify the pattern of occurrence and predicting the Epilepsy Seizure (ES) under an observative asymptomatic patient. The overall prediction bridges the gap between a normalized pattern evaluation and thus computing with abnormal (Epilepsy Seizure) pat- terns under a clinical validation. The research overviews recent approaches to validate and process Epilepsy Seizure and thus the research gaps are identified towards pattern of occurrence evaluation and computing the prediction ratio.

## IV. DUAL MODE EEG OVERLAPPING TECHNIQUE

The Epilepsy Seizure based prediction and oc- currence pattern detection is classified to vali- dated and approve by proposed technique of dual mode EEG overlapping under an observative pat- tern of neural networks, the technique is validated using SVM based classifier for pre-processing and aligning the datasets.

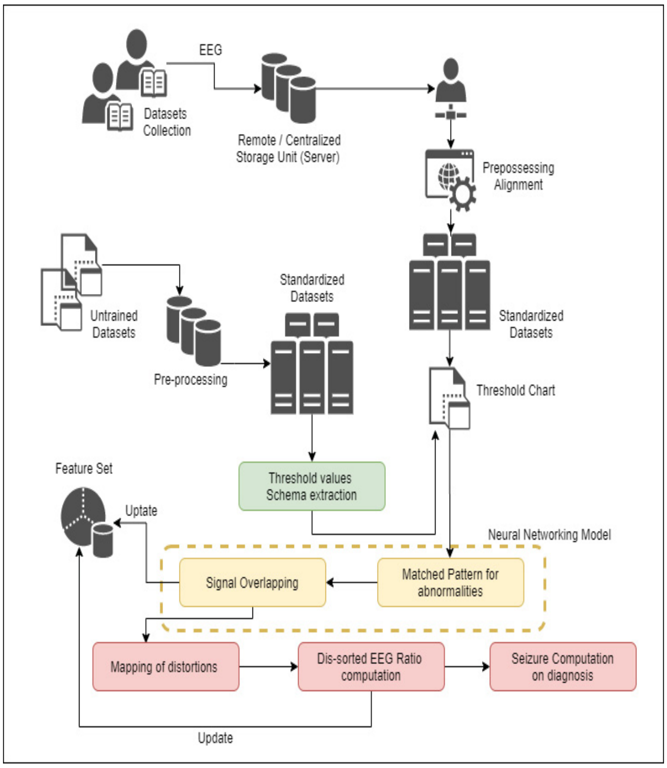


Fig. 1. Dual Mode EEG Overlapping technique for ED diagnosis

The data sets are classified using two independent modules and henceforth, the training of data set is achieved. Each of the classified and trained data set is validated with an informative approach of data standardization. The proposed technique validated data (EEG) under textural standardization format. The standardization provides the stability and reliability on processing data sets. Each of the data set in EEG is further validated using a standardization threshold of data sets with a generation of threshold charts from cross-validation under the process termed as “Primary Database Training and Classification (PDTC)”. On demand, when the patients undergo attack of ES, the recordings are undertaken using EEG reading, each time the system observation are drawn with secondary processing and classification achieved.

Each of the two classification are physically processed and standardization to attain a reliable processing platform. Parallel processes of threshold value in distortions are computed using the regression shift analyzer of dynamically retrieved EEG datasets. Using Neural Networking model, the overlapping of normal verses abnormal is strained and processed to obtain a symmetrical value of distortion in pattern of EEG standardization datasets. The process of overlapping and mapping the distortions are studied using echope of each

EEG datasets and regression change in time intervals, the mapping is further processed and re-validated using EEG ratio computation and feature diagnosis.

Thus, the resulting values are sorted and computed in the trivial alignment using SVM of each feature with respect to the change analysis in neural networking model. The same can be further expanded and validated under models of Training and Classification (T&C Unit), Generation of Threshold charts and data standardization (GTDS Unit), and followed by Neural Networking and Computation Unit as discussed in Section 5.

## V. MATHEMATICAL MODELING OF ES REDICTIONS

Based on the reference of Fig. 1, the proposed model is accurate into six modules of implementation and thus, EEG dataset consisting of values $E = \{E_1, E_2, E_3 \dots E_n\}$ where $E_n$ is $n^{th}$ EEG set value of consider data samples. Consider, the universal dataset of EEG (dynamic) as $E_U$ consisting both normal and abnormal ES based datasets. The normal ES datasets are represented using the vector $E^N$ and abnormal $E^{AN}$. Thus $E_U = \left[\left\{E^N \cap E^{AN}\right\}\forall E \in E_i\right]$ where i is a finite number of datasets. Henceforth, the value of dataset elements $E_U = \left[E_i(n) \subseteq E\right]$ as $E_U$ processes the dependencies of EEG datasets.

### A. *Training and Classification*

The dataset of EEG signal under training *(T)* is considered with respect to $E_U$ of EEG textural datasets. The proposed technique requires the system to be provided with a trained and classified dataset as follows in Eq. 1 and Eq. 2

$$T = \sum_{i=o}^{n} \frac{\delta\left(E_U\right)_i}{\delta t}\sqrt{2\theta}\int_0^k\left[\left(E_k\right)\phi\left(E_{k-1}\right)\right]$$

$$\therefore T = \sqrt{2\theta}\sum_{i=o}^{n}\frac{\delta\left(E_U\right)_i}{\delta t}\left(\int_0^k\left[\left(E_k\right)\phi\left(E_{k-1}\right)\right]\right)$$

Where, $T$ is the trained vector of datasets provided to EEG *($E_U$)*. The value vector $E_K$ is the intermediate low pass filters and high pass filter *(k-1)* wavelets towards alternation processing. Thus, the resultant value *(T)* provides a primary training set and thus on further processing, the classification and training is conducted parallel. On a result of Eq. 2, the classification *(C)* represented as $C_n = \{C_1, C_2, C_3 \dots C_n\}$ as in Eq. 3 and Eq. 4 respectively.

$$C_n = \int_o^n \frac{L(T_i)}{L(t)}.(C_n \phi C_{n-1}).T(E_U)$$

$$C_n = \int_o^n \frac{L(T_i)}{L(t)}.\sum_{i=o}^{n}\left[(E_U)_i \cap (E_z)_i\right]$$

Eq. 3 and Eq. 4 are repeated cyclic and form the overall training and classification data sets. The process can be

$$C_n = \int_o^n \frac{L(T_i)}{L(t)}.(C_n \phi C_{n-1}).T(E_U)$$

simplified and represented as vector (P) representing in Eq. 5

The process (P) is all process as $P = \{P_1, P_2, P_3 \dots\}$ providing an unambiguous training set.

### B. *Data Standardization*

Standardization is the process of stream lining the EEG datasets into a smaller and understandable format.

$$F = \frac{1}{2\pi}\int_0^n \frac{\delta\left(P_S\right)}{\delta t}.2\partial\left(C_n\right)$$

Under standardization, the classified datasets *(P)* are considered under a notation vector *($P_S$)* towards all datasets in order of $(P_S \subseteq P) \in C_n$. The EEG datasets are lined under textural datatypes and thus the classified pattern *($P_S$)* can be validated towards returning the ambiguous and feature extraction. Thus, consider the feature *(F)* in *($P_S$)* vector as shown in Eq.6 The resulting feature *(F)* can be represented under a cyclic set of threshold value charting and represented as $F = \{F_1, F_2, F_3 \dots F_n\}$, where, *'n'* is last dataset of EEG under the standardization format.

### C. *Generation of Threshold Charting*

Threshold charting is considered under a dynamic order of processing towards EEG sample in user comparative fashion, the occurrence of Epilepsy Seizure is under-defined challenges and hence on comparative analysis. The threshold value provides a clear understanding in selecting a corner of evaluation in smallest changes of flexes in EEG samples. Since the samples of evaluation are evaluated by a simple patient under normal and abnormal scenario. Since, threshold charts vary from one cycle of computation to another, consider *(T)* is as demonstrated in Eq.7

$$T = \sum_{i=0}^{n}\left[\frac{\delta\left(F\right)_i}{\delta t} \Rightarrow \int_0^n F_i.\left(E_U\right)_i\right].$$

Threshold values are saturated only in dynamic evaluation process and henceforth, the resulting *(T)* vector needs to address each feature validation via $E_U$ datasets. As represented in Eq. 8 and Eq. 9.

$$T = \lim_{n\to\infty}\left[\sum_{i=0}^{n}\left(\frac{\delta\left(F\right)_i}{\delta t}.\frac{\delta\left(E_U\right)_i}{2\pi}\right)\right]$$

$$\therefore T = \frac{1}{2\pi}\lim_{n\to\infty}\left[\sum_{i=0}^{n}\left(\frac{\delta\left(F\right)_i}{\delta t}\delta\left(E_U\right)_i\right)\right]$$

The supporting vector of all parametric feature evaluations processed and extracted in end of cycle as shown in Eq. 9. In order to evaluate the signal datasets, the threshold (T) supports towards building a reliable vector set as PS = {PS1, PS2, PS3 …} such that, $\{(PS \subset P) \subset EU\}$ on evaluation front.

### D. *Neural Networking Model for EEG Overlapping*

On successfully retrieving the patterns, feature of a standardized EEG datasets, the evaluation of threshold value and its charting is done. Thus, making the signal optimized and ready to evaluate over a neural networking model as shown in Fig. 2. The linkage resolution (LR) is computed to achieve a ordered dataset of neural networking model as represent in Eq. 10. Here, the trivial computation is reflected as an interlocking nit of process evaluation as shown in Eq. 10, where, the data interpretation is reflected into multiple cross linkages operations. The reflected (LR) causes the dataset (EU) to be distorted as each feature vector in universal and trained datasets are evaluated with respect to {L(F) → d(EU)} at a generalized order.

$$L_R = \left\{ \left( \sum_{i=0}^{n} \int_{\infty} E_i \frac{\delta (E_U)_i}{\delta t} \right) \rightarrow \left( \frac{L(F)_i}{L\, t} L(E_U)_i \right) \right\}$$

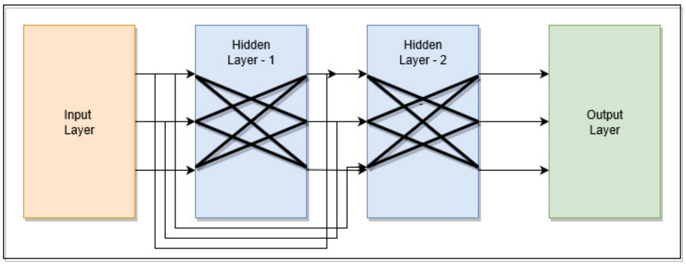


Fig.2. Neural Networking Model for Linkage Resolution

The overlapping phase in linkage resolution (LR) creates a lapping point (LP) using the threshold value charted (T) such that, Π (LP ≠ Tj) and each of Tj for a random resembling point causes a deflection in computational matrix. The overlapping vector of EEG datasets and features are mapped under neural networking model, the terminology of feature set inter-section is reflected as shown in Eq. 11. The LP from Eq.11 is reflected

$$L_P = \left\{ \left( \lim_{\delta x \to 0} \int_{i=0}^{n} \frac{\delta \left(E_U\right)_{Si}}{\delta t} \right) \rightarrow \left( \frac{\delta (t)}{\delta (f_i)} \right) \right\}$$

into multiple directions of EEG datasets and henceforth, the data validation is processed as shown in Eq.12. The validated dataset with respect to feature set is cross-verified with represented vector of classified set *(c)*

$$L_P = \left\{ \left( \lim_{\delta x \to 0} \int_{i=0}^{n} \frac{\delta \left(E_U\right)_{Si}}{\delta t} \right) \rightarrow \left( \frac{\delta (t)}{\delta (f_i)} \right) \right\}$$

Thus, the validated (LP)V vector and its occurrence is computed to achieve the histogram value of distortion.

### E. *Computational Behavioral Change in ES Symptoms Detection*

The evaluation parameters and validated set *($L_P$)* is studied and hence computation of behavioral changes in EEG dataset is studied as an area of distortion, with respect to the value of overlapping, retrieved from Eq. 12 under *($L_P$)* matrix. The ratio of differences are computed as shown in Eq. 13 under the vector of *($B_Z$)* The resultant computational behavioral model *($B_Z$)* is thus explained with dual mode overlapping as shown in Eq. 13 and Eq. 14

$$B_Z = \left( \frac{\lim_{n \to \infty} \int_{i=0}^{\infty} \left[ \frac{\delta \left(L_P\right)_{V_i}}{\delta t} .2\pi\phi \left(E_U\right)_i \right]}{\lim_{n \to \infty} \int_{i=0}^{\infty} \left[ \frac{\delta (f)_i}{\delta t} \cdot \frac{1}{2\pi} \phi \left(E_U\right)_{T_i} \right]} \right)$$

$$B_Z = \frac{1}{4\pi} (E_U) \cap \left[ \lim_{n \to \infty} \int_{i=0}^{\infty} \left[ \frac{\partial (L_P)_{V_i}}{\partial (f_i)} \right] \right]$$

### F. *Occurrence Computation*

Based on behavioral computation *($B_Z$)* vector the order of Epilepsy Seizure *(ES)* occurrence is evaluated as discussed in results section. The occurrence computation is relatively a mathematical certainty as the threshold charting and feature play a vital role. Typically, the system model is designed to compute the average detection as shown in Eq. 15.

$$\left(B_Z\right)_O = \sum_{i=0}^{n} \left[ \left(B_Z\right) \in \left(E_U\right) \right]$$

## VI. RESULTS AND DISCUSSIONS

The EEG signal correction over the dual mode overlapping is processed and discussed mathematically in previous section. The processing EEG signal is inter-dependent and thus overlapping process generates the fraction of distortion of signals under changing ratio of frequencies. In Fig.3, the dual model EEG signal overlapping is processed. Under processing, the signal is converted with a ratio of computation of frequency validation (Right). The frequencies are interpreted as changing fluxes in neuron communications and hence the concerns are highlighted with respect to jumping ratios of frequencies and distortions are recorded.

Changing flexes are recorded in Fig. 3 (Left) over a clear distinction between normal and abnormal signals. The ratio of computation is clear in terms of signal feature extraction and signal classification. The process of classification is adhered in Fig 4 and Fig. 5 respectively. In Fig.4 the signal is over-ridded on abnormal and similarly reversed in Fig.5 to observe the slightest change in signal frequency and flexes. The region of consorted is considered to be the region of interference and signal cancellation to form a jump or seizure occurrence region (SOR).

The changing frequency and the features set is calculated in Fig. 6, thus signal classification-based patterns are extracted and demonstrated in Fig. 7. The outputs are predominant in highlighting the SOR towards constituting the occurrence pattern of Epilepsy Seizure. The data-samples are re-filtered to form a clear classified pattern and ratio of Epilepsy Seizure occurrence in an asymptomatic patient's datasets.

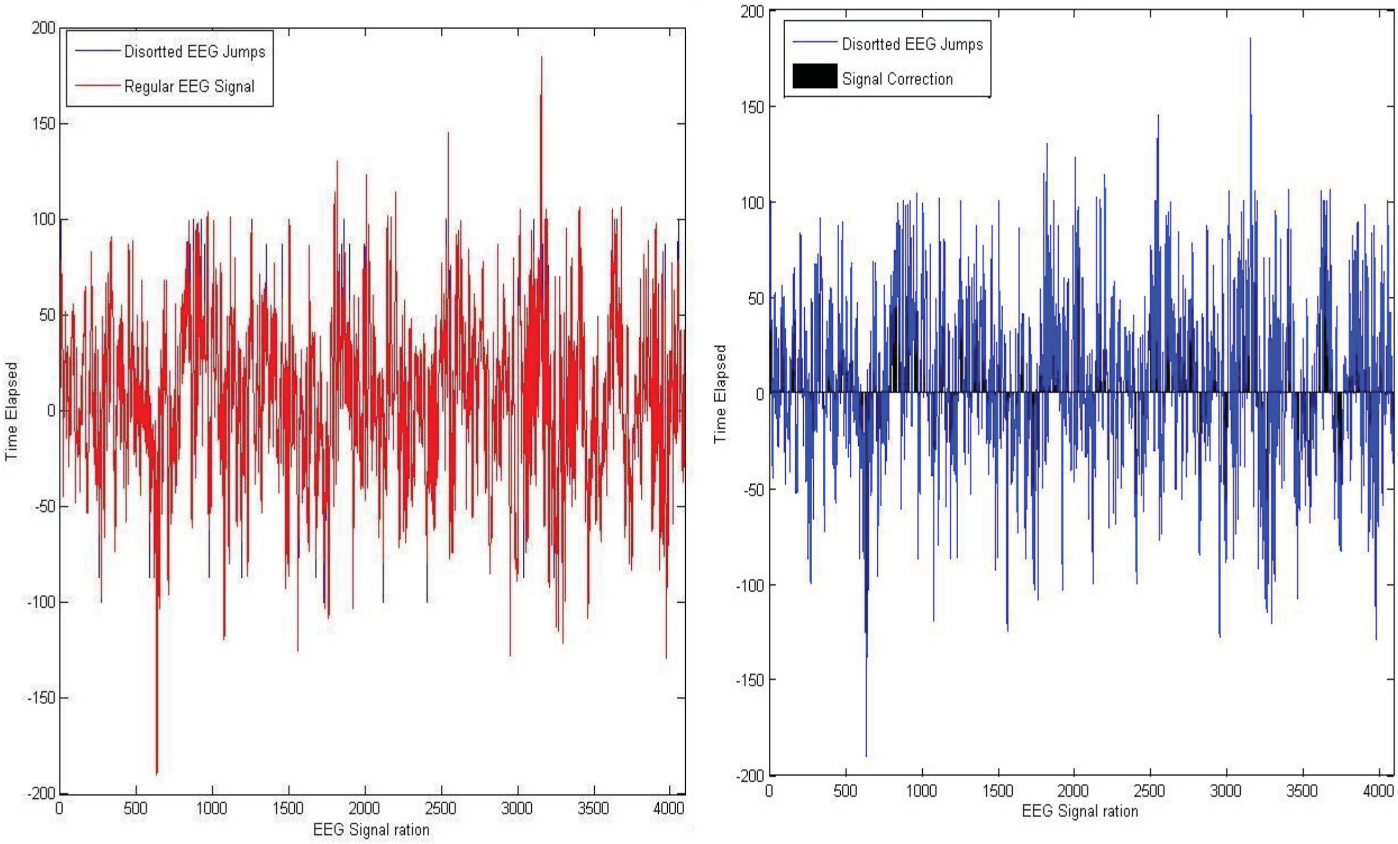


Fig:3. (Left) Dual EEG Signal overlapping, (Right) Distortion EEG signal over signal correction of ES under Overlapping

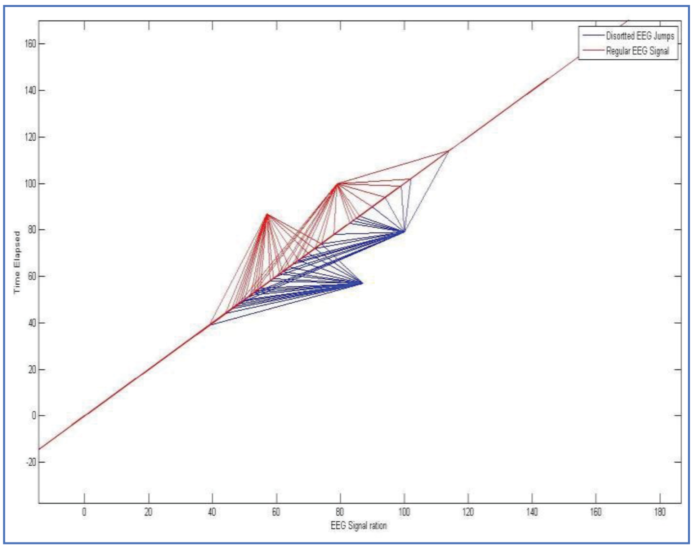


Fig.4. EEG Signal Distortion with comparative dual mode overlapping technique – Right View

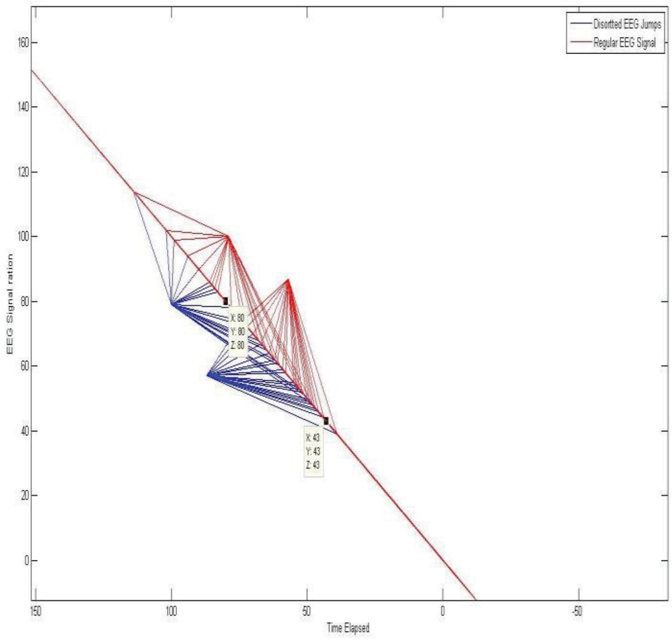


Fig.5. EEG Signal Distortion with comparative dual mode overlapping technique – Left View

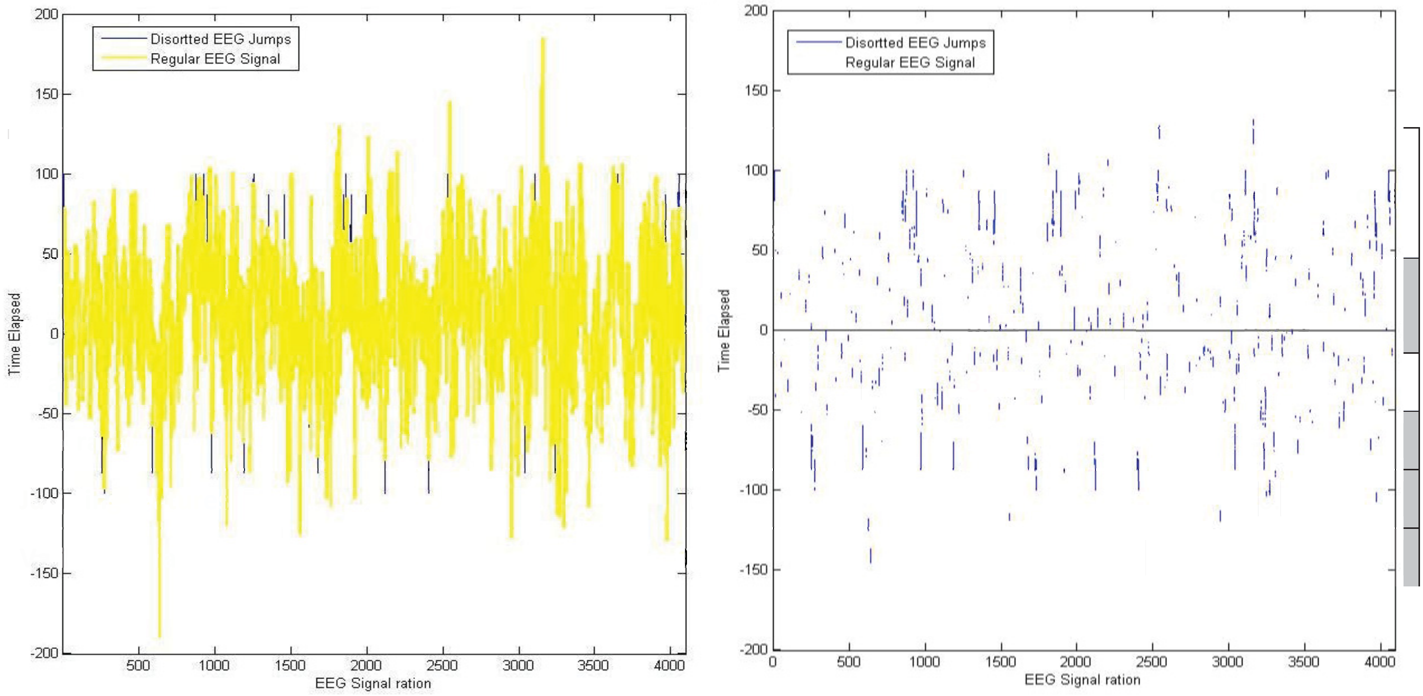


Fig:6. (Left) EEG Signal Jumping under ES, (Right) ES Extraction for computation under occurrence pattern

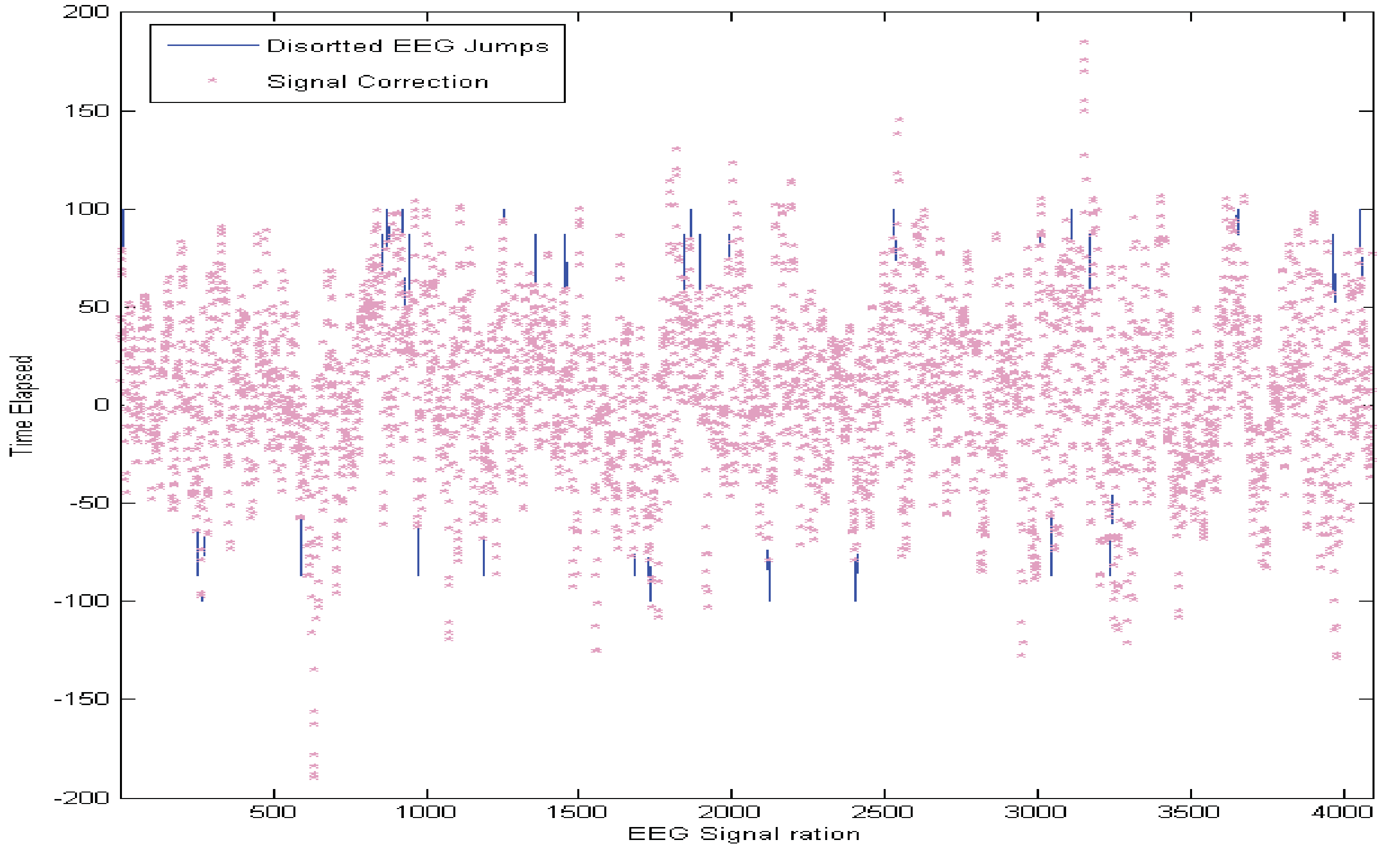


Fig.7. ES Extraction and Jumping extraction of EEG Signal from Dual Mode Extraction

TABLE I. COMPARATIVE ANALYSIS AND EVALUATION OF PROPOSED TECHNIQUE

| Attributes | Normal Occurrence | Abnormal Occurrence | Predictive Occurrence | Proposed Technique Occurrence |
|---|---|---|---|---|
| Occurrence pattern range | 7.86 | 8.86 | 8.34 | 8.391 |
| Feature of distortion | 3.2 | 4.12 | 3.98 | 3.7 |
| Flux ratio | 7.21 | 8.21 | 7.98 | 8.1 |
| Jumping features | 2.3 | 6.8 | 4.9 | 6.1 |
| Validation ratio | 93.4 | 91.87 | 94.2 | 97.32 |

## VII. CONCLUSION

EEG based Epilepsy Seizure pattern extraction using dual mode overlapping is proposed in this article. The technique has successfully extracted the signal jumps or distortion ratio of processing signal with respect to feature sets. These feature sets are further classified into smaller feature vectors until similar patterns of two EEG's is overlapped. The overlapping EEG is sematic and processing datasets are examined to dual mode recursive iterations under negative and positive views as shown in Fig. 4 and Fig. 5. Such that, FN, FP ratio over TN, TP ratio is extracted, the distorted signal range of EEG signal of Epilepsy Seizure occurrence is further highlighted in Fig. 7, such that, occurrence pattern can be justified and extracted. Thus, the proposed technique has successfully evaluated over both normal and abnormal EEG datasets of an asymptomatic patient.

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