



## EVALUATION OF BRAIN TUMOR CLASSIFICATION TECHNIQUES ON IDENTIFICATION OF EEG IN MEDICAL IMAGES

Swathi Dasi<sup>1</sup>, T. Mahalakshmi<sup>1</sup> and K. Srinivasa Rao<sup>2</sup> and Rama Krishna Merugumalli<sup>2</sup>

<sup>1</sup>Electronics and Communication Engineering, PVP, Siddhartha Institute of Technology, India

<sup>2</sup>Electronics and Communication Engineering, Andhra Loyola Institute of Engineering and Technology, India

E-Mail: [dswathi289@gmail.com](mailto:dswathi289@gmail.com)

### ABSTRACT

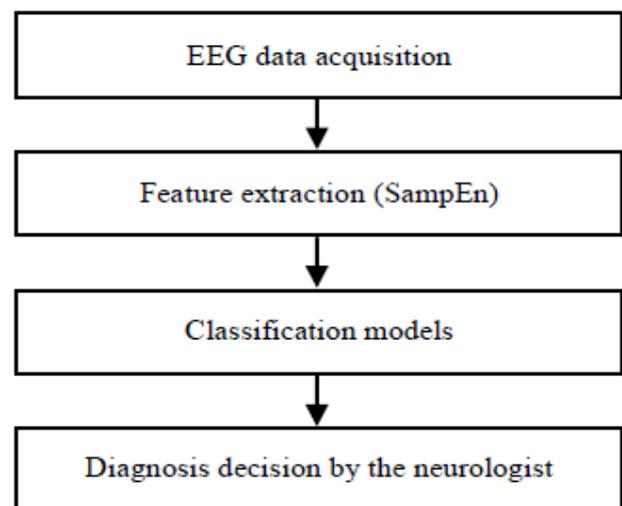
Electroencephalogram (EEG) signal extraction is an arising idea in finding of Epilepsy. Epilepsy is the major neurological problem around shows up in one to 100 people groups experiencing last a long time in Electroencephalogram. A tremendous measure of information delivered by EEG signal observing gadgets and envisions investigation of EEG information portrayal. Anyway, discovery or ID of epilepsy to address EEG waveforms by visual examination, parcel of exploration work on bio-clinical climate. For arrangement and ID of EEG are the significant perspective continuously clinical applications. In this paper, examine about various arrangements related different savvy calculations/techniques for the distinguishing proof of epilepsy in mind or eye-related clinical pictures. Likewise portray the examination of various methodologies/strategies used to recognition or distinguishing proof of bio-clinical pictures.

**Index terms:** epilepsy, electroencephalogram (EEG), classification, feature extraction, principle component analysis and epileptic seizure detection.

### 1. INTRODUCTION

Epilepsy is a neurological issue impacting around 1% of the complete people (around 50 million people) [1]. An epileptic seizure can be depicted by techniques for paroxysmal occasion of coordinated movements. This kind of seizures can fundamentally be isolated into two classes to the extent that the level of relationship of different psyche fields: midway seizures and summarized seizures. Partial seizures start from an illustrated field of the psyche, normally called epileptic foci. Constrained by their sort, they might actually debilitate mindfulness. Summarized seizures incorporate most fields of the frontal cortex and may cause loss of mindfulness and muscle compressions or solidness. Electroencephalography (EEG) is a critical clinical instrument, checking, diagnosing, and supervising neurological messes related to epilepsy. In connection with various philosophies, for instance, Magneto encephalography (MEG) and Functional Magnetic Resonance Imaging (fMRI), EEG is an ideal, monetarily adroit, and safe framework for checking the mind activity.

Notwithstanding open dietary, medicine, and cautious treatment options, at this point around one out of three epilepsy patients can't be managed. They are absolutely dependent upon the unforeseen and unexpected seizures which significantly influence their step by step life, with momentary debilitements of acumen, talk, motor control, memory just as awareness.



**Figure-1.** Representation of EEG signal extraction.

Various new medicines are being explored and among them the most reassuring are implantable devices that pass on direct electrical excitement to affected domains of the frontal cortex. These medications will amazingly depend upon strong estimations for seizure recognizable proof to perform satisfactorily. Since the start of the seizures can't be expected in a short period, a reliable re-cording of the EEG is needed to recognize epilepsy. However, assessment by visual examination of long narratives of EEG, to find traces of epilepsy, is redundant, drawn-out and astonishing cost. In this manner, electronic revelation of epilepsy has been a target of numerous specialists for a surprisingly long time. Computers have for a long while been proposed for dealing with this issue and appropriately, customized restorative genuinely steady organizations for recognizing electroencephalographic changes have been being scrutinized for quite a while. The whole framework can be



isolated into two modules: highlight extraction and course of action (showed up in Figure-1). The introduction of customized observing structures relies upon both the part extraction procedures and the gathering computations associated. As of quite recently, yet various ways of thinking have been created for modified epileptic seizure area, there is no composing explicitly adding to the review of progress of customized restorative sincerely strong organizations utilized for EEG-based epileptic seizure disclosure. In this audit, we rapidly research different procedures used in this re-look for field and portray their essential properties.

## 2. REVIEW OF RELATED WORK

In this part, we present a short review of seizure-related phrasing, the seizure acknowledgment composing, and the one-class Support Vector Machine (SVM)

### 2.1 Seizure-Related Terminology

Seizure assessment suggests through and through to estimations for seizure revelation, seizure assumption, and modified focus station recognizing verification. These examinations are chiefly performed on the EEG. In this assessment, examinations were finished on the intracranial EEG (IEEG), which has astonishingly better spatial objectives, higher sign-to-fuss extent, and more vital bandwidth than scalp EEG. Exactly when various channels are thought of, the cathode region that shows the most prompt verification of seizure development is named the middle channel. It is invaluable to portray parts of the EEG banner by their transient proximity to seizure activity. The ictal period insinuates the time during which a seizure occurs. The interictal period is the time between moderate seizures. The unequivocal electrographic beginning (UEO) is portrayed as the most prompt time that a seizure occasion is clear to an epileptologist seeing an EEG without prior data that a seizure seeks after; the unequivocal clinical beginning (UCO) is the earliest time that a seizure occasion is clear by apparently watching a patient. Seizure starting in this paper is inseparable from UEO. It is critical that the UEO frequently goes before the UCO by a couple of moments, and that various as of late circulated papers described "seizure starting" as the UCO.

### 2.2 Seizure Detection

Early undertakings to recognize seizures began during the 1970s (Viglione, Ordon, and Risch, 1970; Liss, 1973) Furthermore, primarily considered scalp EEG records to recognize the clinical (and less a significant part of the time) electrographic start of seizures. In 1990, Gotman reported a methodology for automated seizure recognizable proof that refined 76% area accuracy at 1 Fp/hr for 293 seizures recorded from 49 patients (Gotman, 1990). In 1993, it was shown that the concise range implies Teager essentialness could be utilized to recognize seizures from electrocorticograms (Zaveri, Williams and Sackellares, 1993). Their locator achieved 100 percent revelation accuracy on a 11-seizure information base. In 1995, Qu and Gotman showed an early seizure forewarning system arranged on design EEG activity that

refined 100 percent area precision at a mean acknowledgment torpidity of 9.35 seconds and bogus alarm pace of 0.2 Fp/hr (Qu and Gotman, 1995). Tantamount results were moreover declared using time- and repeat region features gathered by a k-nearest neighbor classifier (Qu and Gotman, 1997). In 1998, Osorio *et al.* declared 100 percent area affectability with mean disclosure inactivity of 2.1 seconds using a wavelet-based measure called seizure power. They separated a data set of 125 patients, yet the same data was used for getting ready and endorsement (Osorio, Frei, and Wilkinson, 1998). Yet again the estimation was even more comprehensively researched in 2002 using separated electrocorticogram accounts, 100 percent affectability was represented, with distinguishing proof latencies stretching out from 1.8 - 31.1 seconds (Osorio *et al.*, 2002).

A couple of compelling undertakings at seizure revelation using fake neural framework classifiers have been represented beginning around 1996 (Khorasani and Weng, 1996; Webber *et al.*, 1996; Gabor, 1998; Esteller, 2000). Evaluation of 31 specific features (Esteller, 2000) showed that fractal estimation, wavelet group essentialness, and mean Teager imperativeness were especially reassuring for seizure disclosure. In 2001, Esteller reported a finder subject to the line length feature that refined mean acknowledgment dormancy of 4.1 seconds at a sham alert pace of 0.051 Fp/hr (Esteller *et al.*, 2001). A total of 111 seizures (various subclinical) was used for endorsement. NeuroPace, Inc., along these lines, itemized a similar finder reliant upon this work achieved 97% affectability at a mean acknowledgment torpidity of 5.01 seconds (Echaz *et al.*, 2001). This finder was evaluated on 1265 extensive stretches of IEEG data, yet was tuned heuristically in a patient-express way. The NeuroPace marker cases address the bleeding edge in seizure disclosure execution. Progressively complete studies of the seizure area and assumption composing are open elsewhere (Litt and Echaz, 2002; Gardner, 2004).

### 2.3 Novelty Detection

Customary portrayal plans rely upon observational risk minimization estimations to decide "amazing" models for a portrayal decision limit; taking everything into account, they are leaned to over-or underfitting. Additionally, their show will, as a rule, be incredibly sensitive to boundary tuning and researcher inclination. Genuine learning theory addresses a primary danger minimization (SRM) model that changes the trade-off between incredible observational execution (i.e., gathering precision on planning data) and extraordinary hypothesis limit (i.e., course of action precision on subtle data). One well known usage of SRM is the SVM, first showed in 1992 (Boser, Guyon and Vapnik, 1992). The fundamental idea behind the SVM is to find a hyperplane in a part space that "preferably" segregates two classes. Various other straight learning machines have been considered for this task; nevertheless, the SVM yields a stand-out game plan that can be seemed to restrict the typical risk of misclassifying hid points of reference (Vapnik, 1999). Planning estimations to incorporate the



course of action of a comprehended improvement issue, constrained quadratic programming that is computationally compelling and yields overall courses of action. A couple of extraordinary informative activities give recorded settings and nuances on the SVM (Borges, 1998; Bennett and Campbell, 2000; Müller *et al.*, 2001).

In 1998, Schölkopf *et al.* familiarized an extension with SVMs to measure the assistance of scattering (Schölkopf *et al.*, 1999). Their motivation was to unwind a smoothed out transformation of the thickness assessment issue, e.g., finding a base volume quantile assessor that is "essential." The plan they met up at, the one-class SVM, was introduced for peculiarity acknowledgment.

### 3. EEG ANALYSIS METHOD

#### 3.1 EEG Examination Procedures

During the seventies, EEG examination proposed translating the EEG waveform using unquestionable and heuristic methods [21]. On schedule, various procedures have been used to take apart a couple of subtle changes in the EEG signal. Most of the procedures fall under four general arrangements: (1) time-space, (2) repeat region, (3) time-repeat space, and (4) nonlinear techniques.

##### 3.1.1 Time-space procedures

The critical procedures for time-space examination are immediate assumption and part examination. Figure-2 shows the common EEG waveforms in time-space having a spot with a commonplace individual and epilepsy open-minded in the octal and interracial states.

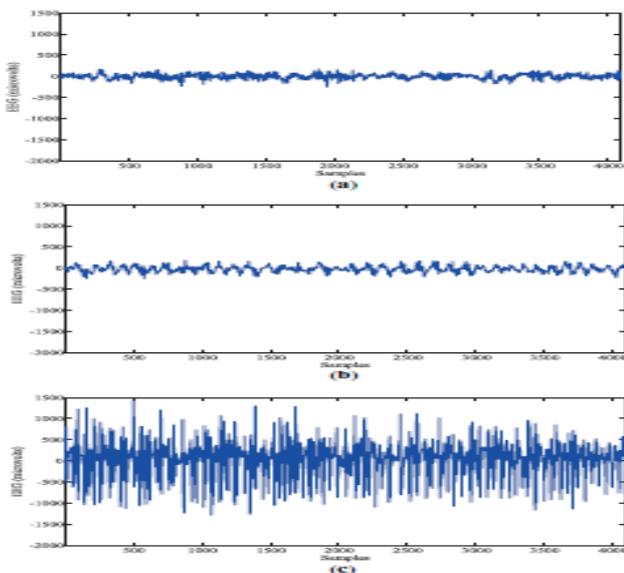


Figure-2. Interracial states representation in EEG signal extraction.

##### 3.1.1.1 Linear Prediction (LP)

In this strategy, the yield of a straight system is expected ward on data  $x(n)$  and past yields  $y(n-1), y(n-$

$2), \dots, y(np)$  as showed up in the going with condition Here 'a' and 'b' are called pointer coefficients and  $\hat{y}(n)$  is the measure of  $y(n)$ . From above Eq., obviously, the measure is comparable to an immediate blend of past yield regards close by over a critical stretch of time data regards

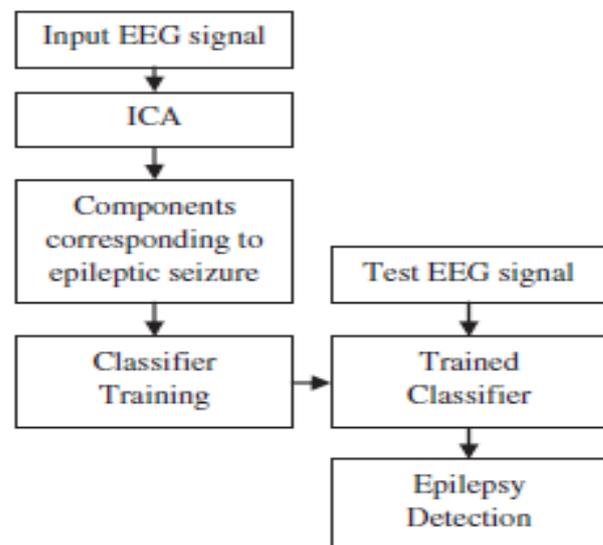


Figure-3. ICA epilepsy detection procedure.

##### 3.1.1.2 Part analysis

Fragment assessment is a solo procedure to depict educational records to a rundown of abilities. Significant, straight, in addition, free-part examinations are the procedures for section examination used in epilepsy analysis [22].

##### 3.1.1.2.1 Principal Component Analysis (PCA)

PCA changes the high-layered data to a low-layered even part (Eigenvector) subspace so the planning is ideal in a total squared slip-up since. All of the balanced features is called an 'fundamental part'. The most essential contrast in the data set is gotten by the super essential part. The accompanying essential change is gotten constantly key part.

The subsequent key part is directionally inverse to the super chief section. The assessment of the part of the feature space depends upon the appointment of data centers around the data set. In PCA, the removed feature subspace is straight. Ghosh-Dastidar *et al*, Subasi and Gursoy and Acharya *et al* used PCA for the gathering of epileptic EEG signals.

##### 3.1.1.2.2 Independent Component Analysis (ICA)

ICA expects that each intentional sign is an immediate mix of the independent sign. It stalls the multi-layered data vector straightforwardly to quantifiably independent sections. ICA can be satisfactorily used to oust antiquated rarities and to separate EEG recorded sign into different portion sign started from different sources.

Concerning epilepsy revelation, ICA is used to eliminate the free subcomponents contrasting with



epileptic seizure from the mix of EEG signals. The isolated subcomponents are by then used to plan classifiers that get to know the difference between commonplaces moreover, epileptic areas. This strategy is displayed in Figure-3. A test EEG sign can be a commitment to a pre-arranged classifier to recognize the closeness of any seizure affected areas in it.

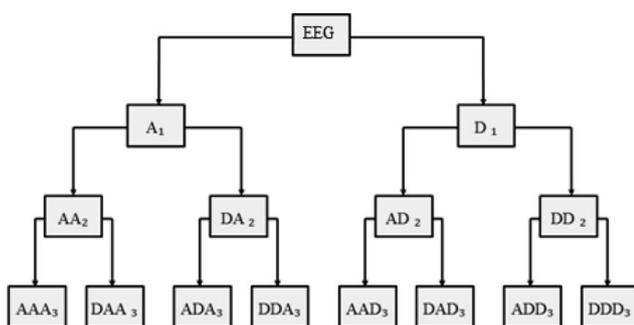
### 3.1.1.2.3 Linear Discriminate Analysis (LDA)

Like PCA, LDA is one more consistently used framework for the lessening of dimensionality. LDA causes dimensionality decline by observing a straight mix of features that can segregate no less than two classes.

This immediate mix can fill in as a straight classifier. LDA models the qualification between classes of data. LDA helps the extent of progress between classes to the distinction inside the class in the data set. LDA doesn't change the region of the principal instructive assortments, regardless, gives more division between classes. Kaplan pondered with regards to the time-moving spooky characteristics of the epileptic EEG waveform and calculated the real boundaries in time region. Subasi and Gursoy used the time region strategies for PCA, ICA and LDA to diminish the dimensionality of repeat region boundaries for recognizing epileptic EEG.

### 3.1.1.2.4 Recurrence region methods

The phantom examination is a point by point assessment of information contained in the repeat region by using authentic and Fourier Change (FT) methods. Spooky assessment strategies can be arranged as (1) the old style or non-parametric strategy and (2) the non-old style or parametric approach. Non-parametric technique. In this technique, autocorrelation is at first assessed from a period sequenced educational list. The accompanying stage is control range assessment by applying FT to the autocorrelation gathering. The Welch system is typically used to evaluate the power scope of a period gathering. In the Welch method, a data window is associated with each segment of the time progression to isolate the time game plan into moderate squares, and the period gram is outlined for each square, finally, the period grams are tracked down the center worth of after some an ideal opportunity to choose the measure of the Power Spectral Density (PSD).



**Figure-4.** Wavelet transforms of packet representation in EEG signal extraction.

## 3.1.2 Time-repeat region methods

### 3.1.2.1 Wavelet change

A wavelet is somewhat surge of restricted term moreover, restricted imperativeness which is related with the EEG sign to get the wavelet coefficients. Right away, the mother wavelet (a reference wavelet) is moved continually along the time scale to get a ton of coefficients at all snapshots of time. The wavelet coefficients address the sign in both the time and repeat spaces. Then, the wavelet is extended for a substitute width and after that normalized to contain a comparable proportion of essentialness as the mother wavelet. By then, the chief strategy of moving this extended wavelet along the time scale and surveying the relating set of coefficients is done. Discrete Wavelet Transform (DWT), Continuous Wavelet Transform (CWT) and Wavelet Packet Decomposition (WPD) are the three sorts of wavelet changes. Jahankhani *et al*, Sadati *et al*, Subasi *et al* and Ocak *et al* used DWT in their work for the robotized area of epilepsy. Acharya *et al*. [3] used WPD for recognizing epileptic stages using Higher Order Spectra (HOS) cumulants. WPD is an increase of the DWT. In the example of DWT, in the principle aspect, the sign is rotted into coarse assessment coefficients by isolating it using a low-pass channel and into detail coefficients by going it through a high-pass channel. In the ensuing aspects, the rot is done recursively on the low pass surmise coefficients gained at the past aspect. The system continues for the necessary number of levels. Regardless, because of WPD, both the detail additionally, surmises coefficients are rotted at each aspect. A layout of WPD is given in Figure-4. A1 depicts the assessment coefficients got at level 1 of disintegration and D1 the detail coefficients. Furthermore, AA2 and DA2 are the gauge and detail coefficients gained at level 2 by rotting A1. These coefficients can be used as features that depict the epileptic activities.

### 3.1.3 Nonlinear technique for examination

Repeat space methods can get melodic movements in a sign, yet are obliged by the inability to perceive nonlinear coupling, also, stage getting among music in a comparative reach. Normal structures can be addressed in a fruitful way using nonlinear frameworks. This is substantial for EEG signal assessment also. The various qualities and endeavored nonlinear boundaries for the revelation of epilepsy using EEG sign are HOS, Largest Lyapunov Example (LLE), Correlation Dimension (CD), Fractal Dimension (FD), Hurst Exponent (H), entropies like Approximate Entropy (ApEn) and Sample Entropy (SampEn), and Recurrence Quantification Investigation (RQI). In this section, we rapidly portray these boundaries.

## 4. COMPARISON OF DIFFERENT APPROACHES

In this section, we describe about traditional approaches used in automatic detection of epilepsy in EEG with different feature representations. Description shows in Table-1 with different accuracy levels.

**Table-1.** Summary of different approaches used in EEG classification.

Authors	Features	Classifier	Accuracy (%)
Nigam and Graupe	Nonlinear pre-processing filter	Diagnostic neural network	97.20
Kannathal et al.	Entropy measures	Adaptive Neuro-Fuzzy Inference system (ANFIS)	92.22
Srinivasan et al.	Time & frequency domain features	Elman network	99.60
Sadati et al.	DWT	Adaptive neural fuzzy network	85.90
Subasi	DWT-Statistical measures	Mixture expert model (a modular neural network)	94.50
Polat and Gunes	FFT based features	Decision tree	98.72
Tzallas et al.	Time-frequency methods	Artificial neural network	97.72-100
Srinivasan et al.	ApEn	Probabilistic neural network, Elman network	100
Polat and Gunes	FFT based features	Artificial immune recognition system	100
Polat and Gunes	AR	C4.5 decision tree classifier	99.32
Ocak	DWT-ApEn	Thresholding	96.65
Guo et al.	Relative Wavelet Energy	ANN	95.20
Guo et al.	ApEn and Wavelet Transform	ANN	99.85
Guo et al.	Line length features and Wavelet Transform	ANN	99.60
Subasi and Gursoy	DWT-PCA, ICA, LDA	SVM	98.75(PCA) 99.50(ICA) 100(LDA)
Ubeyli	AR	SVM	99.56
Lima et al.	Wavelet Transform	SVM	100
Guo et al.	Genetic programming based	KNN	99
Wang et al.	Wavelet packet entropy	KNN	100
Iskan et al.	Cross correlation and PSD	Several classifiers including SVM	100
Orhan et al.	DWT	ANN	100

## 5. SCOPE OF THE RESEARCH

Diagnosing epilepsy needs securing of patients' EEG recording and gathering extra clinical data. A lot of information are delivered by EEG checking gadgets and examination by visual assessment of long accounts of EEG to observe hints of epilepsy isn't regularly imaginable. Investigation into programmed recognition frameworks for epilepsy has been progressively well known during these years. The issue of sign grouping for epileptic seizure identification is considered as a common pat-tern-acknowledgment issue which incorporates include extraction and order.

In view of above conversation connected with order of EEG from natural eye related information, essentially centered around following exploration destinations:

- Empirical De-piece based Classification Approach (EDCA) for the examination of unusual epileptic seizure signal from human mind pictures. EDCA assesses natural mode capacities (IMF), it extricate various highlights acquired from IMF for arrangement of strange epileptic seizure recognition utilizing least square help vector machine (L-SVM) classifier with various span predisposition capacities (RBF). RBF gives best exactness of arrangement to proposed approach as for epileptic seizure EEG extraction from human cerebrum pictures
- Hierarchal Machine Learning Approach (HMLA) which is the blend of Grasshopper Optimization Algorithm (GOA) and Support vector machine (SVM) for programmed seizure recognition in EEG. It is separated and assessed various boundaries to prepare sweep predisposition portion work classifiers with various documentations. Grasshopper Optimization Algorithm is utilized investigate viable subset of elements and afterward ideal boundaries in view of

SVM for fruitful order of EEG. Further improvement of proposed approach, it gives better EEG arrangement and upgrade determination of epilepsy with viable exactness 90-100 % with examination of ordinary information and epileptic cerebrum picture information.

## 6. CONCLUSIONS

In this paper, we momentarily explored various strategies created for programmed epileptic seizure location and portray their basic properties. Different component extraction methods based on recurrence space investigation, time-recurrence area examination and complex examination were talked about; individually and grouping models utilized for planning clinical emotionally supportive networks of programmed epileptic seizure discovery were additionally examined. Then again, despite the fact that consistency of epileptic seizure starting from human intracranial and scalp EEGs has been supported, more investigations should be directed for expanding the precision of forecast.

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