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UTILIZING GENETIC ALGORITHMS WITH DIMENSIONALITY REDUCTION TECHNIQUES FOR EPILEPSY CLASSIFICATION FROM EEG SIGNALS

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Abstract:

The Electroencephalography (EEG) signals play an important and crucial role in the accurate diagnosis of epilepsy. To detect the epileptic activities is quite a demanding and challenging task which requires an in depth analysis of the entire recordings of the EEG data. Such a type of analysis can be done only with the help of EEG experts, highly experienced in visualization of the EEG data. The EEG recordings are too long and contain an enormous amount of data to be processed. So in this paper, the size of the data is reduced using certain dimensionality reduction techniques like Fuzzy Mutual Information (FMI), Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA), Linear Graph Embedding (LGE) and Variational Bayesian Matrix Factorization (VBMF). Automated classification techniques and algorithms have made great strides and serve as a boon for biomedical engineers and doctors. In this paper, the dimensionally reduced values are being classified with the help of Genetic Algorithm (GA) for the perfect classification of epilepsy from EEG signals. The benchmark parameters analyzed here are Specificity, Sensitivity, Time Delay, Quality Values, Performance Index and Accuracy.

Keywords: EEG, FMI, ICA, LDA, LGE, VBMF

1. Introduction

One of the most commonly occurring brain disorders is epilepsy [1]. The main characteristic of epilepsy is that the epileptic seizures occur in recurrent and sudden incidences for the patient and as a result, it leads to life-threatening situations for the person. Due to the unexpected electrical disturbances in the brain, the seizures occur and the excessive neuronal discharges can be clearly identified in the EEG signal. For the clinical assessment of the brain and to detect the epileptic seizures, EEG signals are widely used [2]. With the aid of visual scanning of the EEG of an epileptic patient, the detection of epileptic seizures is quite tedious and time consuming process. An expert is also required to interpret the lengthy EEG recordings to detect and analyze the epileptic activities. So the existence of reliable automatic classification algorithms came into existence. With the help of automatic classification algorithms, the diagnosis of epilepsy is significantly improved [3]. These classification algorithms serve as a best friend to epileptic patients who are taking anti epileptic drugs for a long time and suffering from the drug's neurological and cognitive side effects. The chances of the visual expert of EEG to misread and misinterpret the data are narrowed down.

A lot of EEG automated signal classification techniques have been proposed in literature. The concept of detecting various seizures using computerized system was proposed by Gotman [4]. To predict the epileptic seizure onset from the epileptic EEG recordings, Gigola et.al applied the concept of accumulated energy evolution using wavelets [5]. The scope for the non linear time series is discussed by Adeli et.al [6]. A back propagation neural network with Autoregressive (AR) and periodogram features as inputs for detection of the seizures was done by Kigmiket et.al [7]. A basic classification methodology using wavelet analysis and Radial Basis Function (RBF) network was proposed by Ghosh-Dastidar et.al [8]. The application of Approximate Entropy as inputs to an Artifical Neural Network Classifier was presented by Srinivasan et.al [9]. The mixture of experts along with the wavelet analysis applied to the Artificial Neural Network to classify the epileptic EEG signals was done by Subasi et.al [10]. Sunil Kumar Prabhakar and Harikumar Rajaguru reduced the dimensionality of the EEG signals and Classified with the help of Gaussian Mixture Models (GMM) [11]. In this paper the dimensionality reduction techniques and the use of Genetic Algorithms are incorporated to classify the epilepsy from EEG signals. The organization of the paper is as follows. In section 2, the materials and methods are discussed followed by the usage of dimensionality reduction techniques in section 3. The application of Genetic Algorithm as a Post Classifier is dealt in section 4 followed by the results and conclusion and at the end the conclusion is presented.

2. Materials and Methods

The raw EEG data for totally twenty epileptic patients are taken for the study. The readings of the patients were collected from Sri Ramakrishna Hospital, Coimbatore, India when the patients were admitted in the neurology department for treatment. The pre-processing stage is given a high priority here because it is important to get all the useful information from the EEG signals which are non linear and non stationary in nature. The recordings were done totally for thirty minutes and the EEG records are taken continuously for about thirty seconds and it was divided into two second epoch because this short duration is more than enough to identify the unnecessary redundancy and trace other significant necessary changes. There are totally sixteen channels employed for all the patients and it is measured for over three epochs simultaneously. The maximum frequency is 50 Hz and the sampling frequency is kept as 200 Hz because the sampling frequency should be twice greater than the maximum frequency. For each epoch there are around 400 values obtained. The artifacts present here is around 1% which included EMG, motion artifacts, eye blinks and chewing artifacts. Figure 1 shows the block diagram of the paper

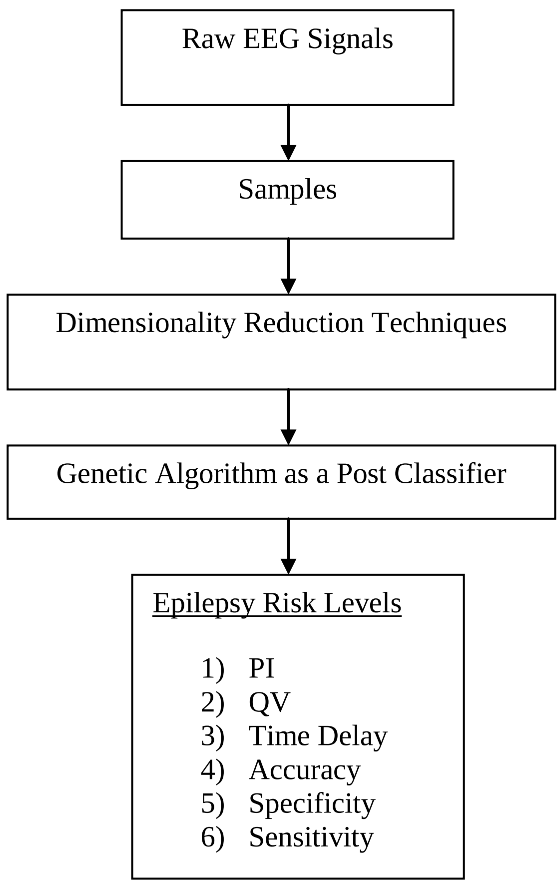

Figure 1 Block Diagram of the Paper

3. Dimensionality Reduction Techniques

In general practice, one has to know the sufficient features necessary to solve the specific problems but it is difficult to understand and get the knowledge apriori which features will be thoroughly utilized. The feature selection or the dimensionality reduction techniques play an important role here. The primary aim of dimensionality reduction is to achieve the reduction in the feature matrix size [12]. This step involves eliminating some features thereby drastically reducing the unnecessary data consumption and storage. Secondly, with the help of dimensionality reduction, the computational cost is easily improved and the performance of the classification algorithms too is enhanced greatly. In this paper, FMI, ICA, LGE, LDA and VBMF are utilized to reduce the dimension of the data.

A. Fuzzy Mutual Information:

The FMI is mainly engaged as a dimensionality reduction technique because it always deals with the uncertainity in the data. Between each variable and the class feature, the information relationship is established and it is assessed with the help of measurement of FMI [13]. In each and every step, the features containing the highest values of the Resident Mutual Fuzzy (RMF) information of the feature class is added in the feature subset. This final step always depends on the real value parameter β, which tells the actual way the residual information is computed as shown in the following equation, where $'S'$ denotes the set of features chosen

$$RMF(f,C) = MF(f,C) - \beta \oplus_{sf \in S} MF(f,sf)$$

where f is a feature in the domain that has not been selected and C is the feature class. If the number of features is increased, then the RMF is effected more by the variables which are noisy. In those cases, the random variables are included in the feature subset and it is not related to the features present in S. Thus the low dimensional features are obtained.

B. Independent Component Analysis

It is an example of information theory based dimensionality reduction algorithm [14]. It is a generative model with the following equation

$$a = Z\chi$$

The Principal Component Analysis (PCA) always searches and finds the uncorrelated factors while ICA seeks and finds for the independent factors. If the factors are truly independent, then it is definitely an advantage of ICA. In the context of ICA, the χ vectors are named as sources, meanwhile $'a'$ is termed as the observation. The mixing matrix is termed as Z and the problem is developed as one of the source separation. The main idea is to find an unmixing matrix $\tilde{Z}$ such that the components of $\hat{\chi} = \tilde{Z}^t a$ are very independent. The sources can be recovered to scale changes and permutation changes.

C. Linear Graph Embedding

It is a similar technique to Isomap, where a graph representation is constructed with the help of data points [15]. It also preserves the local properties and so it is least sensitive to the problem like short circuit which occurs in Isomap. The non convex manifolds are successfully embedded with the preservation of local properties. In LGE, a set of the nearest neighbours of each and every point is found out initially. Then a set of weights is computed for each and every point that describes the point as a total linear combination of its neighbours.

For a data set consisting of N vectors as $X_{1,}X_2 ...., X_N$ each having a dimensionality D. Initially the neighbours of each data point X_i is computed. Then the corresponding weights W_{ij} which best reconstructs each data point from its respective neighborhood is found out. The reconstruction error is measured by the cost function as

$$E(W) = \sum_i \left| X_i - \Sigma_j W_{ij} X_j \right|^2$$

where the weights W_{ij} deals the contribution of the i^{th} point to the j^{th} reconstruction.

D. Linear Discriminant Analysis

LDA finds to reduce the dimensionality of the data while it preserves the class discriminatory information as much as possible [16]. It is assumed that a set of D dimensional samples $\{x_1, x_{2,} .... x_N\}$ are present where N_1 belongs to the class w_1 and N_2 belongs to class w_2. A scalar $'y'$ is found out by projecting the samples $'x'$ onto a particular line as,

$$y = w^T x$$

Of all the lines, one line which maximizes the separability of the scalars is selected. Then to find a good projection vectors, the measure of separation is defined. In x-space and y-space, the mean vector of each class is defined. In x space and y space, the mean vector of each class is defined as follows

$$\mu_i = \frac{1}{N_i} \sum_{x \in w_i} x$$

$$\hat{\mu}_i = \frac{1}{N_i} \sum_{y \in w_i} y$$

$$\mu_i = \frac{1}{N_i} \sum_{x \in w_i} w^T x = w^T \mu_i$$

The objective function J is then chosen as the distance between the projected means as

$$J(w) = |\hat{\mu}_1 - \hat{\mu}_2| = |w^T(\mu_1 - \mu_2)|$$

E. Variational Bayesian Matrix Factorization

As dimensionality reduction is a basic preprocessing step done to change the dimensions of the data from higher level to a lower level, Variational Bayesian Matrix Factorization Technique is also used here [17]. Consider $'C'$ as a low-rank matrix. The matrix $'C'$ is then decomposed into the product of $D = (d_1, d_2, ...d_H)$ and $F = (f_{1,} f_2 ..... f_H)$

Therefore the equation can be written as

$$C = FD^T$$

If the obtained matrix is denoted as Q and if it is prone to the additive noise model, then

$$Q = C + \varepsilon$$

where ε is a noise matrix

For the Bayesian matrix factorization, the Gaussian priors on the parameters D and F is used and is represented as follows

$$\phi(C) = \phi_D(D)\phi_F(F)$$

The Bayes posterior $P(D, F|Q^n)$ can be written as follows

$$P(D, F|Q^n) = \frac{P(Q^n|D, F)\phi_A(A)\phi_B(B)}{\langle P(Q^n|D, F)\rangle \phi_A(A)\phi_B(B)}$$

where $\langle . \rangle_p$ denotes the expectation over P

For VBMF trial distribution [17] the equation is expressed as follows

$$r(D, F|Q^n) = \prod_{n=1}^{H} r_{d_n}(d_n|Q^n) r_{f_n}(f_n|Q^n)$$

4. Genetic Algorithm as a Post Classifier

The merits of applying Genetic Algorithm (GA) for optimization and classification is tremendous [18]. A simple GA is as follows:

1) A randomly generated population of totally n chromosomes are started.

2) The fitness value of each chromosome is computed

3) From the initial population, a pair of parent chromosomes is selected.

4) Crossover operation is performed to produce the two offsprings with a probability P_{cross}.

5) With a probability P_{mut}, the mutation of the two offsprings is carried out.

6) The offsprings are then replaced in the population

7) The termination condition is checked or else step 2 is repeated.

Each iteration in the above mentioned steps is called as a generation. The termination range is usually fixed from 50 to 500 or more. After each generation, global minimum check is done and then the algorithm can be terminated when this condition is achieved. Only with a finite parameter space, genetic algorithm works. To optimize cost due to parameters that consider only finite number of values, this characteristic is ideal. To optimize continuous parameters, the concept of quantization can be applied. Such a consideration allows a simple crossover and mutation procedure that operates on the chromosomes.

The iterations which are involved in successfully implementing the GA ensures that the GA should drastically reduce the error rate. It also makes sure that the individual with the best fitness value is picked since each chromosome has to report the exact error rate involved and finally the GA picks up the smallest of error rate. The fitness function is given as follows

$$fit = \frac{\alpha}{N_f} + \exp\left(\frac{-1}{N_f}\right)$$

α = kNN-Based classification error.

N_f = Cardinality of the dimensionally reduced features.

The algebraic structure of this equation ensures that the error is minimized and there are reduced number of features selected which aids in the successful implementation of the GA. Table 1 shows the simulation parameters of GA classification used in this study.

Table-1: Parameters of GA.

Parameters	Description
Population size	100
Maximum number of evaluated individuals	2500

Type of selection	roulette-wheel
Type of mutation point	mutation
Type of crossover	one-point (2 parents)
Type of replacement	elitist
Generation gap	0.8
Probability of crossover	0.5
Probability of mutation	0.5
Probability of changing terminal	non-terminal

5. Results and Discussion

For the dimensionality reduction techniques and GA as a Post Classifier, based on the Quality values, Time Delay and Accuracy the results are computed in Tables II respectively. The formulae for the Performance Index (PI), Sensitivity, Specificity and Accuracy are given as follows

$$PI = \frac{PC - MC - FA}{PC} \times 100$$

where PC – Perfect Classification, MC – Missed Classification, FA – False Alarm,

The Sensitivity, Specificity and Accuracy measures are stated by the following

$$Sensitivity = \frac{PC}{PC + FA} \times 100$$

$$Specificity = \frac{PC}{PC + MC} \times 100$$

$$Accuracy = \frac{Sensitivity + Specificity}{2} \times 100$$

The Quality Value Q_V is defined as

$$Q_V = \frac{C}{(R_{fa} + 0.2) * (T_{dly} * P_{dct} + 6 * P_{msd})}$$

where C is the scaling constant,

R_{fa} is the number of false alarm per set,

T_{dly} is the average delay of the onset classification in seconds

P_{dct} is the percentage of perfect classification and

P_{msd} is the percentage of perfect risk level missed

The time delay is given as follows

$$\text{Time Delay} = \left[2 \times \frac{PC}{100} + 6 \times \frac{MC}{100} \right]$$

The Specificity and Sensitivity Analysis for the application of dimensionality reduction technique followed by the application of GA as Post Classifiers is shown in Figure 2. The Time Delay and Quality Value Analysis for the application of dimensionality reduction technique followed by the application of GA as Post Classifiers is shown in Figure 3. Similarly the Performance Index and Accuracy Analysis for the application of dimensionality reduction techniques followed by the application of GA as Post Classifiers is shown in Figure 4. It is evident when when Fuzzy Mutual Information acts a dimensionality reduction technique followed by GA as post classifier the accuracy is around 93.88% followed by ICA with GA as 93.50%. A high quality value is also found in FMI-GA combination as of 18.40 as of other combinations. Table III shows the related work comparison with our work.

Table-II: Comparison Performance Values for the different dimensionality reduction algorithms with Genetic Algorithms as Post Classifiers.

	FMI	ICA	LDA	LGE	VBMF
PC (%)	87.77	87.01	86.52	86.59	85.13
MC (%)	00625	0.48	0.76	0.55	0.76
FA (%)	11.59	12.5	12.70	12.84	14.09
PI (%)	85.43	84.22	83.56	83.38	81.34
Sensitivity (%)	88.40	87.5	87.29	87.15	85.90
Specificity (%)	99.37	99.51	99.23	99.44	99.23
Time Delay (sec)	1.79	1.76	1.77	1.76	1.74
Quality Value	18.40	18.18	18.03	18.18	17.90
Accuracy (%)	93.88	93.50	93.26	93.29	92.56

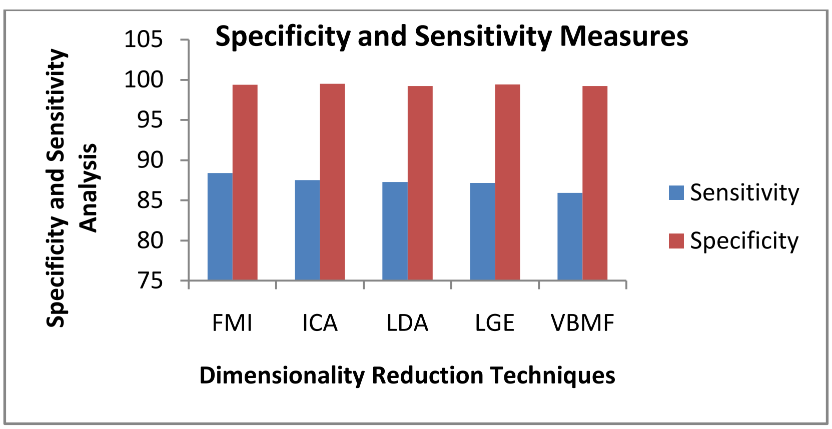

Figure-2: Specificity and Sensitivity Measures.

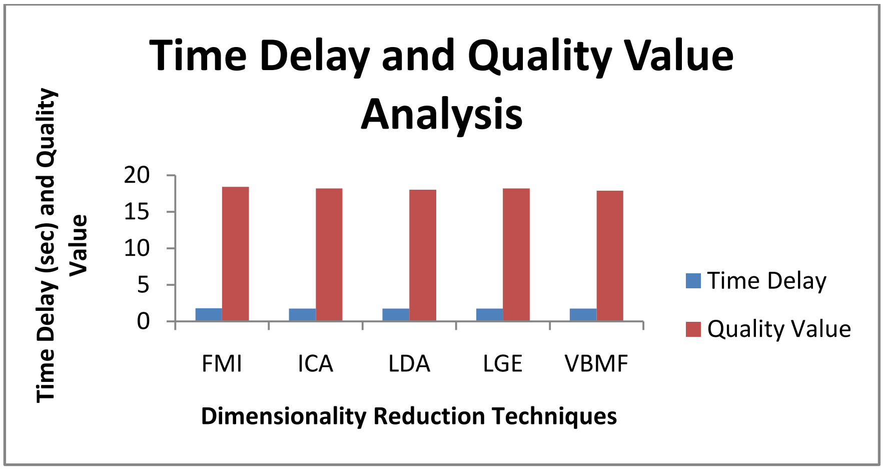

Figure-3: Time Delay and Quality Value Measures.

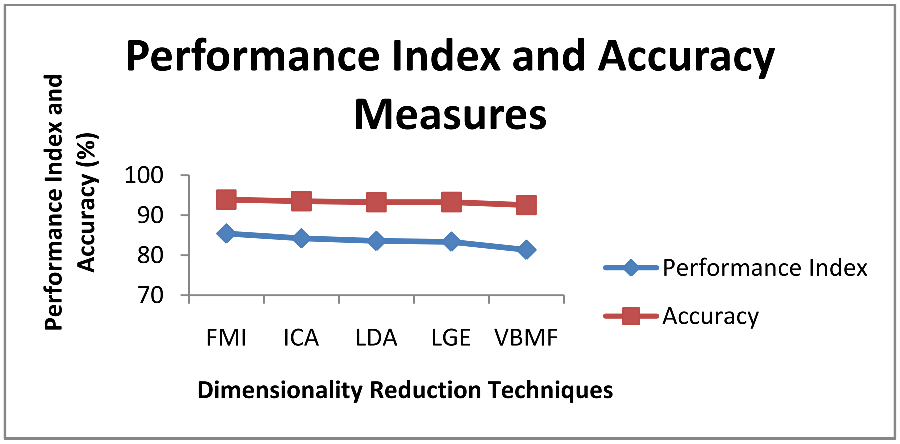

Figure-4: Performance Index and Accuracy Measures.

Table-III: Related Works Comparison with our work.

S.No	Year	Method	Accuracy	Authors
1	2005	Lyapunov exponent, Recurrent Neural Networks	97%	Guler et al [19]
2	2006	Wavelet Transforms, adaptive neuro-fuzzy networks	86%	Sadati et al [20]
3	2007	Wavelet transform, chaos analysis, k means clustering	97%	Dastidar et al [8]
4	2008	Higher Order spectra, Gaussian Mixture Model	93%	Chua et al [22]
5	2011	Genetic Programming, K means neighbour classifier	93%	Guo et al [23]
6	2013	Db 2 Wavelet Thresholding , SVD	98.04%	Harikumar et al [24]
7	2015	Fuzzy Mutual Information , GMM	97.84%	Sunil Kumar Prabhakar et al [11]

6. Conclusion

Thus the most used technique to capture the brain signals are the EEG signals. EEG is considered as a highly complex human brain signal which consists of valid information about the functions of the brain and the other neurological disorders. Epilepsy occurs due to abnormalities in the genetic mechanisms of humans or it may be due to developmental anomalies and infections in the central nervous system. It is quite difficult to extract the feature rhythms because the EEG signal is quite complex, stochastic and non-stationary in nature. Due to the abrupt and unpredictable nature of the epileptic seizures, the everyday routine life of an epileptic patient is severely affected. Since epilepsy is witnessed by sudden disturbances of the mental functions which results due to the excessive discharging of groups of cells in the brain, the epileptic EEG obtained from the scalp is characterized by synchronized periodic waveforms which have very high amplitude. Spikes and sharp waves too are found in between the seizures and hence the detection of it by an encephalographer is quite difficult as it requires skilled technicians who are in great demand nowadays. This leads to a prolonged diagnosis time period and also the expenditures related to it is too much to bear. Surgery may not be suitable to all the patients because it demands the consideration of the other health risks also. Therefore, the seizures have to be detected in an automatic manner and it forms an integral part of biomedical research. This research on epilepsy has therefore become an active interdisciplinary field of biomedical research. Thus the dimensions of the EEG signals were reduced using five different dimensionality reduction techniques and then it was classified by using Genetic Algorithm as Post Classifier. Results showed that FMI-GA gives the best result with an accuracy of about 93.88%. Future works is to use different kinds of genetic algorithms to find out the best classification procedure for epileptic detection from EEG signals.

References:

1. Freeman, WJ, Holmes, MD, Burke, BC &Vanhatalo, S 2003, 'Spatial spectra of scalp EEG and EMG from a wake human', Clinical Neurophysiology., vol.114, pp.1053-1068.
2. Easwaramoorthy & Uthayakumar, R 2010.Analysis of Biomedical EEG Signals using Wavelet Transforms and multiultifractal Analysis", IEEE EMB Magazine vol. 30, pp. 74-87.
3. Gabor, AJ & Seyal, M 1992, 'Automated interictal EEG spike Detection using artificial neural networks', Electroenceph. Clin. Neurophysiol, vol. 83, pp. 271-280.

4. Gotman J, Automatic recognition of epileptic seizures in the EEG, *Electroen Clin Neuro* 54:530, 1982.
5. Gigola S, Ortiz F, Attellis CE, Silvaand W, Kochen S, Prediction of epileptic seizures using accumulated energy in a multiresolution framework, *J Neurosci Methods* 38:107, 2004.
6. Adeli H, Ghosh-Dastidar S, Dadmehr N, A wavelet-chaos methodology for analysis of EEGs and EEG sub-bands to detect seizure and epilepsy, *IEEE Trans Biomed Eng* 54(2):205, 2004.
7. Kiymik MK, Subasi A, Ozcalik HR, Neural networks with periodogram and autoregressive spectral analysis methods in detection of epileptic seizure, *J Med Syst* 28:511, 2004.
8. Ghosh-Dastidar S, Adeli H, Dadmehr N, Mixed wavelet-chaos-neural network methodology for epilepsy and epileptic seizure detection, *IEEE Trans Biomed Eng* 54(9):1545, 2006.
9. Srinivasan V, Eswaranand C, Sriraam N, Approximate entropy-based epileptic EEG detection using artificial neural networks, *IEEE Trans Inf Technol Biomed* 11:288, 2007.
10. Subasi A, EEG signal classification using wavelet feature extraction and a mixture of expert model, *Expert Syst Appl* 32:1084, 2007.
11. Sunil Kumar Prabhakar, Harikumar Rajaguru, " ICA, LGE and FMI as Dimensionality Reduction Techniques followed by GMM as Post Classifier for the Classification of Epilepsy Risk Levels from EEG Signals", 9th IEEE European Modelling Symposium 2015, October 6-8, Madrid, Spain,
12. R.Harikumar, P.Sunil Kumar, "Dimensionality Reduction Techniques for Processing Epileptic Encephalographic Signals", Biomedical and Pharmacology Journal, Vol.8, No.1, 2015, pg no:103-106
13. R.Harikumar, P.Sunil Kumar, "Fuzzy Mutual Information as a Dimensionality Reduction Technique for Epileptic Electroencephalography Signals ", Research Journal of Applied Science, Engineering and Technology, Maxwell Scientific Publishers, Vol.10, No.9, 1035-1037, 2015
14. R.Harikumar, P.Sunil Kumar, "Performance Comparison of EM, MEM, CTM, PCA, ICA, Entropy and MI for Photoplethysmography Signals", Biomedical and Pharmacology Journal, Vol.8, No.1, 2015, pg no: 413-418
15. S.K.Prabhakar, H.Rajaguru, "Application of Linear Graph Embedding as a Dimensionality Reduction Technique and Sparse Representation Classifier as a Post Classifier for the Classification of Epilepsy Risk Levels from EEG

Signals", Proceedings of the International Conference on Graphic and Image Processing (ICGIP), October 23-25, 2015, Singapore.

16. Q. Gu, Z. Li, J. Han, "Linear Discriminant Dimensionality Reduction", Machine Learning and Knowledge Discovery in Databases, Volume 6911 of the series LNCS,pp. 549-564
17. M.Seeger, G.Bouchard, " Fast Variational Bayesian Inference for Non-conjugate Matrix Factorization Models", Proceedings of the 15th International Conference on Artificial Intelligence and Statistics (AISTATS) 2012, PG: 1012-1016.
18. Georges R,Harik, Lobo FG,& Goldberg B, 1999, 'The Compact Genetic Algorithm,' IEEE Transaction of Evolutionary Computation, vol.3, No.4, pp. 287-297.
19. Guler I, Ubeyli ED, Guler I, Recurrent neural networks employing Lyapunov exponents in EEG recordings, *Expert Syst Appl*, 29(3), 2005.
20. Sadati N, Mohseni HR, Magshoudi A, Epileptic seizure detection using neural fuzzy networks, *in Proc. IEEE Intern Conf on Fuzzy Syst*, Canada, 2006.
21. Chua KC, Chandran V, Acharya R, Lim CM, Automatic identification of epilepsy by HOS and power spectrum parameters using EEG signals: a comparative study, *in Proc. IEEE Eng Med Biol Soc*, 3824-3827, 2008.
22. Guo L, Rivero D, Dorado J, Munteanu CR, Pazos A, Automatic feature extraction using genetic programming: An application to epileptic EEG classification, *Expert Syst Appl*, 38:1042, 2011.
23. Harikumar Rajaguru & Vijayakumar Thangavel, 'Performance analysis of wavelet transforms and morphological operator-based classification of epilepsy risk levels', EURASIP Journal on Advances in Signal Processing 2014, 2014:59 doi:10.1186/1687-6180-2014-59.

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