Automatic Processing of EEG signals for Seizure Detection using Soft Computing Techniques

Meenakshi Sood
Assistant professor, ECED,
Jaypee University of Information Technology
Waknaghat, Solan, Himachal Pradesh, India.
meenakshi.sood@juit.ac.in

Sunil V.Bhooshan
Professor, ECED
Jaypee University of Information Technology
Waknaghat, Solan, Himachal Pradesh, India.
sunil.bhooshan@juit.ac.in

Abstract— **Epileptic seizures, a crucial neurological disorder, reflect the excessive and hyper-synchronous activity of neurons in the brain. Human knowledge of functioning of the brain is still insufficient to understand the neurophysiology of suddenly occurring epileptic seizures. But the detection of the disorder and recognition of the affected brain area is essential for the clinical diagnosis and treatment of epileptic patients. Epilepsy is not only a disorder, but rather acts as a syndrome with divergent symptoms involving episodic abnormal electrical activities in the brain. EEG is the most economical and effective tool with high temporal resolution for understanding the complex dynamical behavior and studying physiological states of the brain. The research presented in this paper, aims to develop a computer aided diagnostic system utilizing EEG data to diagnose whether the person is epileptic or not. We present here various methodologies that could be implemented in hardware for monitoring an epileptic patient. Statistical features depicting morphology of EEG signals are extracted, selected and utilized to classify the signals by Artificial Neural Network, Radial Basis Function, Naive Bayes Classifier, K means classifier, Support vector machine. Efficacy of technique is evaluated on the basis of performance measures, sensitivity, specificity and accuracy. It has been observed that artificial neural network and support vector machine with radial basis function kernel are more successful as compared to other soft computing paradigms.**

Keywords- ANN(Artificial neural network; RBF(Radial Basis function); SVM(Support vector machine); Naïve Bayes Classifiers.

I. INTRODUCTION

Epilepsy is a chronic neurological brain disorder characterized by abnormal brain electrical activity which affects about one percent of world population [1]. Epilepsy is a complicated problem due to overlapping symptomatology with other neurological disorders. Epilepsy is one of the most common neurological disorders that greatly impair patient daily lives. The most common way for epilepsy diagnosis is through analysis of EEG. It still remains the main diagnostic modality for absence seizures, even if it is often combined with MRI mostly to rule out false diagnosis related to brain tumor or stroke. Electroencephalography (EEG) is an effective non-invasive tool for understanding the complex dynamical behavior of the brain and for monitoring different physiological states of the brain, neurological disorders.

Scalp EEG has been employed as a clinical tool for the analysis and healing of brain disease [2]. During epilepsy, less number of independent functions and processes are active in the brain. Epileptic seizures can be clearly distinguished from non-epileptic ones by observing the EEG recordings as non-epileptic seizures have normal EEG readings [3].

Traditional epileptic diagnosis relies on tedious visual screening by neurologists from lengthy EEG recording that requires the presence of seizure activities. Usually, confirmation of the diagnosis involves a combination of the medical history of the patient and EEG interpretation by an expert neurologist [4]. The development of accurate and reliable EEG-based automated tools is still in its infancy. Many automated system for accurate and timely diagnosis of epilepsy have emerged [5-7]. Nevertheless, with the advent of new signal processing techniques, there has been an increased interest in the analysis of the EEG for prediction of epileptic seizures. These algorithms can detect abnormal disorder and malfunctioning of the brain not only during the seizure but also can detect the onset of seizure up to some extent. An automatic seizure detection system is used in the diagnosis of epilepsy, which act as an additional tool apart from visual inspection of EEG by the physician [8].

Nigam and Graupe [9] used a multistage nonlinear pre-processing filter along with an Artificial Neural Network (ANN) for the automated detection of epileptic signals. Nonlinear parameters like CD, LLE, H, and entropy were used to characterize the EEG signal [10]. Using the same dataset, the same group automatically classified EEG signals into normal and epileptic using different entropies using an Adaptive Neuro-Fuzzy Interference System (ANFIS) and obtained an accuracy of 92.22% [11]. Adaptive neural fuzzy network was used by [12] to automatically identify. Normal and epileptic EEG signals with a classification accuracy of 85.9% Srinivasan et al. [13] developed an automated epileptic EEG detection system using approximate entropy as the feature in Elman and probabilistic neural networks. Tzallas et al. [14] employed time–frequency methods to analyze selected segments of EEG signals for automated detection of seizure using neural network and obtained an accuracy ranging from 97.72%

The research presented in this paper, focus on EEG signals and validate various detection algorithms in order to develop an automated soft computing diagnostic system that can use EEG data to diagnose whether the person is epileptic. Such a system should also detect seizure activities for further investigation by doctors and potential patient monitoring. To develop a technique to deal with the epileptic seizure prediction problem, useful features are extracted from EEG signals, which represent the brain activity states and performance is reported in terms of accuracy, sensitivity, specificity and applicability in the clinical practice. The paper is organized as follows: Section II discusses about the methodology applied; detailing the clinical data used for the study and various soft computing techniques used for classification. In Section III details of the selection and extraction of the statistical features is elaborated. Section IV gives the discussion and results obtained from the proposed method.

II. METHODOLOGY

A. *Data Acquisition*

The EEG data used in this study is in public domain obtained from University of Bonn, Germany [15]. The complete dataset is obtained from EEG recordings taken by standardized International 10-20 system, containing 100 single-channel EEG signals of 23.6 s duration. All signals were recorded with 128-channel amplifier system using an average common reference, digitized using 12 bit resolution and sampled at a sampling rate of 173.61Hz. The epochs were chosen such that they pass a weak stationary criterion, which makes the data suitable to be used as a whole. Signal of an epileptic patient and a normal patient is shown in Fig 1.

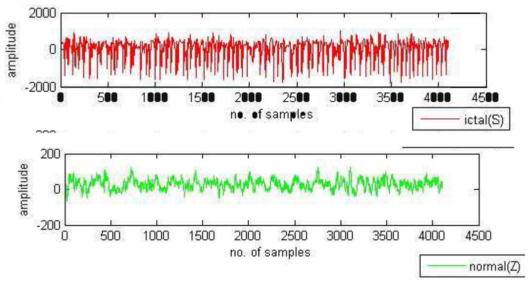

Fig. 1. Signal of epileptic patient and normal patient

B. *Soft Computing Techniques*

Advance methods of signal and data analysis as well as increasing powers of computing, provide improved computing tools to record and analyze the EEG signals. The new techniques have given a detailed insight to study brain mechanisms; computationally strong signal processing techniques have enhanced the accuracy and precision of analysis of signals. The various advanced statistical methods for handling regression and classification tasks with multiple dependent and independent variables tools present are neural networks, support vector machines, Bayes classifiers and many others which have increased powers of computing and provide excellent results when used with computationally strong signal processing techniques.

1) *Support Vector Machine (SVM)*

SVM is primarily a classier method that performs classification tasks by handling multiple continuous and categorical variables and constructing hyper planes in a multidimensional space that separates cases of different class labels [6]. They first try to map the input vector into high dimensional feature space, either linearly or by methods depending on kernel type chosen; such that error is minimized over the training dataset. Then an optimized division is sought between the patients being epileptic or not such the two classes are separated by the largest margin. The SVM allows users to choose from a number of available modes and kernel functions. In all the modules, a default classification mode is used while kernel functions are varied. The kernel functions available are linear, polynomial, radial basis and sigmoid (1, 2). In all the support vector machines the cut-off value used for prediction is 0, i.e. a query vector is regarded as member of positive dataset if its score is greater than 0 and is regarded as member of negative dataset if its score is less than 0 [17]. The ones having scored equal to zero are regarded as undefined. In our work we have used primarily RBF and polynomial kernels functions because of their localized and finite responses across the entire range of the real x-axis

$$k(\mathbf{x_i}, \mathbf{x_j}) = \exp(-\gamma\|\mathbf{x_i} - \mathbf{x_j}\|^2) \tag{1}$$

$$k(\mathbf{x_i}, \mathbf{x_j}) = (\mathbf{x_i} \cdot \mathbf{x_j})^d \tag{2}$$

2) *Naive Bayes*

Naive Bayes is a method primarily formulated for performing classification tasks when the dimensionality of the independent space (i.e., number of input variables) is high. Given its simplicity, i.e., the assumption that the independent variables are statistically independent, Naive Bayes models are effective classification tools that are easy to use and interpret and incorporates a variety of methods for modeling the conditional distributions of the inputs including normal, lognormal, gamma, and Poisson[18]. In effect, Naive Bayes reduces a high-dimensional density estimation task to one-dimensional kernel density estimation.

3) *Multilayer Perceptron neural network (MLPNN)*

MLPNN is composed of a set of sensory units that form the input layer, one or more hidden layers and an output layer consisting of computational nodes. The number of neurons in the input layer symbolizes the data presented to the network. The hidden layer receives inputs from input layer, transforms them into nonlinear combinations and passes the results to the next layer for further processing. The output layer consists of neurons depending upon the outputs required. Neural networks are trained and are capable of solving complex and different problems, but with certain limitations. One or more layers of hidden neurons enhance network’s learning of difficult problems by extracting more significant features from the input vectors (Haykin 1999). There are many training algorithms used to train an MLPNN and a frequently used one is called back propagation (BP) training algorithm [19]. Although the BP algorithm has been a significant milestone in neural network research area of interest, it has been known as an algorithm with a very poor convergence rate. A significant improvement on realization performance is done by using various second order approaches namely Newton's method, conjugate gradient's, or the Levenberg–Marquardt (LM) optimization technique [20-21]. LM can be thought combination of the steepest descent and the Gauss-Newton method.

4) Radial Basis Function (RBF)

The design of a neural network can also be perceived as a curve-fitting (approximation) problem in a high-dimensional space, where learning is viewed as finding a surface which represents a best fit to the training data in a multidimensional space. This multidimensional surface is then used to interpolate the test data. The method of radial-basis functions is motivated by such a viewpoint [22]. A radial-basis function (RBF) network basically consists of three layers having completely different tasks. The input layer connects the network to the environment via source nodes , a nonlinear transformation from the input layer to the hidden layer of high dimensionality is applied in the second layer and the linear output layer, produces the response of the network to the input vector. There is a higher chance of a pattern recognition problem to be linearly separable in a high-dimensional space, so nonlinear transformation is applied prior to a linear transformation and the dimension of the hidden space in an RBF network is made high.

III. STATISTICAL FEATURES

To reduce the dimensionality of the too large EEG signal without losing the useful information embedded in it, features are extracted from the signals. Features are extracted using different techniques summarizing the original signal. The features selected for this study result from thorough review of literature, research efforts and understanding of EEG signal. The signal obtained are "cleaned" by filtering, averaging, thresholding, noise filtering and above all artifact removing. Artifacts due to Electromyogram (EMG), Electrooculogram (EOG), Electrocardiogram (ECG), ballistic effect, and glossokinetic potential can contaminate the measurement and even lead to a false diagnosis. [23].

While selecting the features care is taken to choose the features set which extract the relevant information and hold the maximum amount of variation with respect to the classes, resulting into a correct classification. Two methodologies for features estimation were employed. The first one involves the estimation of statistical features in time and the second methodology involves the estimation of higher order cumulants and non-linear features [24] .In this study thirteen statistical features are selected after extraction in order to investigate the adequacy for the discrimination of three stages of epileptic patient. Entropy is the diminished capacity for spontaneous changes in signals. The signal which shows the least entropy is considered to be seizure state because of least information contained in it, as less number of dominating process are involved [9]. Mean is defined as average value of a distribution of the signal coefficients. Standard deviation provides information about the amount of change of the frequency distribution. The standard deviation of Seizure signal is higher than normal signals. Energy of the signal is defined as the sum of squared modulus of the sample values. In order to evaluate deviation of EEG signals from the normal distribution skew and kurtosis are computed. EEG signal do not follow the normal distribution, and that these coefficients have a heavy tail characteristics [25]. Designing a prediction model with optimum number of features is always desired as it leads to better performance of the classifier in terms of time taken to classify and classification accuracy. Prediction importance of each feature in terms of rank and importance parameter in this study is extracted and depicted in Fig 2.

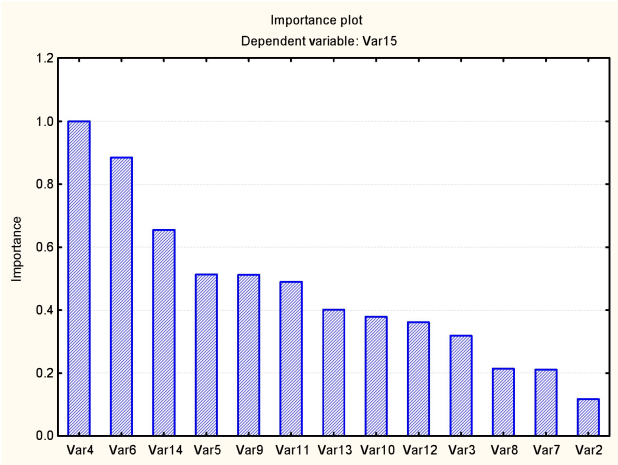

Fig. 2. Prediction importance of each feature in terms of rank

Validation

Most predictive neural network models are prone to over fitting, which means, while the error rate on the training dataset decrease during the training phase, the error rate on the unseen dataset "testing dataset" increases at some point. To overcome this problem, we used the Bootstrapping validation technique with 1000 seed points, by dividing our dataset into training, validation and testing datasets. We split our dataset in 15% for testing and 70% for training and 15% for validation and the error value on the testing dataset offers an unbiased approximation of the generalization ability of the model.

IV. RESULTS AND DISCUSSION

The neural network architecture employed in this study is feed-forward network with thirteen features representing the neurons in the input layer, one hidden layer with five hidden neurons and one output layer with two neurons representing two stages of output. In order to carry out classifications, the networks have been trained with training patterns namely input and output parameters. The activation function used is tan-hyperbolic and softmax for hidden and output layers, with Entropy as error function. The techniques used for training neural networks are the BFGS (Broyden-Fletcher-Goldfarb-Shanno). These methods perform significantly better and require a smaller number of iterations to train a neural network given their fast convergence rate and more intelligent search criterion. The number of hidden neurons chosen is result of exhaustive training of MLPNN with varying number of hidden neurons.It gave 100 % testing and validation accuracy and 100% training accuracy.

In this study while using RBFNN, the Gaussian function and the least squares (LS) criterion are selected as the activation function of network and the objective function, respectively. A network adjusts iteratively parameters of each node by minimizing the LS criterion according to gradient descent algorithm. RBFNN comprises three layers of nodes with the hidden layer being made up of Gaussian or asymmetric kernels [26]. The inputs to the network simply pass each of the input signals to the middle layer kernels and then to output layer. The number of hidden neurons chosen is result of exhaustive training of MLPNN with varying number of hidden neurons. We achieved 99.2 % training accuracy, 100% testing and 93.3 % validation accuracy.

For using SVM as non linear classifiers in this research work, training was performed and various kernels were used linear, quadratic, polynomial, and Gaussian Radial Basis (RBF.) to evaluate which of the proposed kernels had the best performance as a classifier. For Polynomial Kernel with degree=3.000, gamma=0.077, coefficient=0.000, number of support vectors were found to be 91 (84 bounded). The 100% sensitivity of classifying and epileptic patient and 91% for normal patient was achieved. For SVM with Radial Basis Function as Kernel with gamma=0.077, number of support vectors were found to be 26. The 100% sensitivity of classifying and epileptic patient and normal patient was achieved. Evaluation of each confusion matrix is performed computing the efficiency parameters for SVM using each kernel. According to them and considering the application, the best performance was obtained with the RBF kernel.

For the performance evaluation and validity of the proposed method, three key parameters are considered: Sensitivity, Selectivity and Accuracy (4-6) which are evaluated by examining the table that is called as confusion matrix.

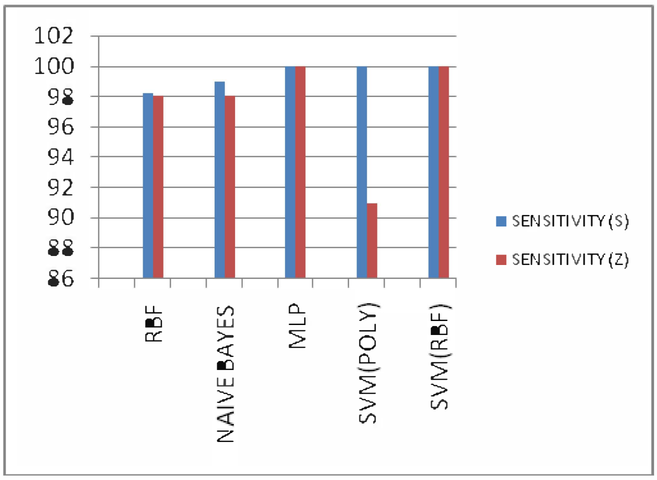

Fig. 3. Sensitivity analysis for the classification of epileptic patient and normal for various the soft computing paradigms

$$Sensitivity = \frac{TruePositive}{TruePositive + FalseNegative} \quad (3)$$

$$Specificity = \frac{TrueNegative}{TrueNegative + FalsePositive} \quad (4)$$

$$Specificity = \frac{TrueNegative}{TrueNegative + FalsePositive} \quad (5)$$

True Positive is defined as the real seizure that was correctly identified; False Positive is assigned to the proportion of non- seizure cases that were incorrectly classified. Observed values for these three evaluation performance statistics are summarized in Table 1a) – e) for all the considered techniques.

TABLE 1. a) Confusion Matrix for a) Naive Bayes b) MLPNN c) RBF d) SVM(RBF) E) SVM(POLY)

a)

Class Predicted	Observed (rows) x Predicted (columns)	
	s	z
s	98	2
z	1	99

b)

Class Predicted	Observed (rows) x Predicted (columns)	
	s	z
s	100	0
z	0	100

c)

Class Predicted	Observed (rows) x Predicted (columns)	
	s	z
s	97	3
z	1	99

d)

Class Predicted	Observed (rows) x Predicted (columns)	
	s	z
s	100	0
z	0	100

e)

Class Predicted	Observed (rows) x Predicted (columns)	
	s	z
s	100	0
z	9	91

MLPNN succeeded in classifying the epilepsy groups with the total classification accuracy of 100% AND SVM with RBF as kernel function gave 100% accuracy. Figure 4 depicts the variation achieved in performance metrics for all the soft computing techniques resulting in MLPNN and SVM (RBF) technique as the best soft computing paradigm for our application. The experimental results show that proposed classifier promises high classification accuracy, good sensitivity and specificity for classifying. The proposed model can assist clinicians for diagnosing different epileptic stages in their earlier stages.

There are a few limitations in the generalizability of these findings to the diagnosis of epilepsy and other disorders. In patients who present with their first seizure, the clinical question is not merely if the seizures are epileptic or non-epileptic: the patient also needs to know if they are at risk for future seizures.

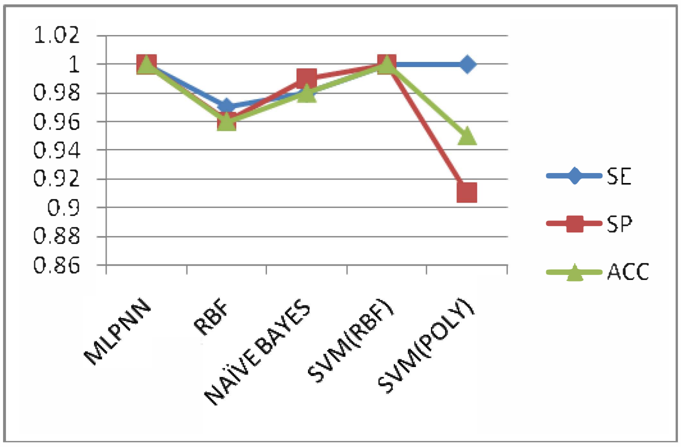

Fig. 4. Variation achieved in performance metrics for all the soft computing techniques.

CONCLUSION

The motivation behind the research reported in this paper is to design a computer aided diagnostic system utilizing EEG data to diagnose whether the person is epileptic or not. The present methodology studies a bi-class problem to show the generalizability of soft computing technique. The deployment of the techniques could be used to get deeper information of EEG associated to epilepsy events in an automatic way. The authors have used this technique to check the feasibility and effectiveness of developing a seizure detection paradigm that can be easily implemented on any embedded system device. The proposed method has potential in designing EEG based diagnostic system for detection of electroencephalographic changes and can be extrapolated even for fault detection in other pattern recognition problems.

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