

Performance Analysis of Classifiers for Seizure Diagnosis for Single Channel EEG Data

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ABSTRACT

The problem of diagnosis and treatment of epileptic seizures to aid neurophysiologists suggests the development of automated seizure onset detection systems. The purpose of the quantitative research is to determine the best classifier having highest rates of classification. This research work compares the classification results between seizure and non-seizure and inters ictal activity using Neural Network, Support Vector Machine and Radial Basis function machine learning techniques. It has been illustrated from results that the neural network classifier outperforms for the present research work. The differences between classification accuracy exhibited by the different classifiers are small, but the superiority of neural network as compared to support vector machine classifier and radial basis function was sustained by classification accuracy, sensitivity, specificity and ROC curve.

Keywords: Electroencephalogram; Neural networks; Support Vector Machine; Receiver Operating Curve.

INTRODUCTION

Various neuro-imaging techniques are available as X ray, angiography, electroencephalogram (EEG), magnetoencephalogram (MEEG) CT scan, ultrasound, single photon emission computed tomography (SPECT) functional magnetic resonance imaging (fMRI), positron emission tomography (PET) to analyze and infer electro physiological phenomenon occurring in human brain¹. Out of these techniques EEG is less expensive, more precise, has excellent time resolution and can be acquired non invasively, which makes this technique more frequently used. The electroencephalogram (EEG) signals provide vital information about the activity of human brain in terms of electrical characteristics. EEG signals are recorded from human scalp as the electrical fluctuations produced on the scalp². These voltage fluctuations are caused by the flow of billions of neurons ionic current that are transported across

the membranes and charge the neurons. The wave of ions reaches the electrodes on the scalp and produces the voltage difference that is measured by voltmeter whose readings are measured as the EEG potential. Neuron generates too small of a charge and it is the summation of thousands of neurons acting synchronously, possessing similar spatial orientation which is measured as EEG signal.

As EEG signals are non-invasive electrical brain signal, they are captured with the help of electrodes placed on the scalp (sometimes in form of a cap) at specific locations. Electrodes are cup-shaped with EEG gel that acts as an interface material between the electrode and the skin as there is no direct contact between skin and the electrode material. The electrodes provide enough volume to contain an electrolyte and capture the electrical signal³.

So the resultant signal developed at the terminals is collected by the electrode and passed on to the electronic circuitry. The standard method used by EEG machines to describe the location of scalp electrodes is "10-20" system. This is an International Standard of placing and positioning of the electrodes on the human scalp for measuring brain activity⁴. The "10" and "20" refer to the distances between adjacent electrode that are either 10% or 20% of the total front-back or right-left distance of the skull. Each electrode placed at the scalp is identified by a letter F, T, P and O for frontal, temporal, parietal, and occipital respectively and a specific number is allotted to identify the hemisphere location. The odd numbers 1,3,5,7 represent left hemisphere and even numbers 2,4,6,8 represent right hemisphere as depicted in Figure 1.

Epilepsy is characterized by abnormal electrical activity in the brain and is considered as recurring neurological brain disorder⁵. Epileptic seizure is result of excessive and hyper synchronous firing of large number of neurons in the brain. Sudden and excessive neural activity leads to epileptic seizures that are sudden, brief and recurrent. During seizure, occurrence of strange sensations, change in emotions convulsions and loss of consciousness are noticed⁶.

EEG is one of the main diagnostic tests for epilepsy and an effective clinical tool for monitoring, diagnosing and prognosis of neurological disorders. The onset of a clinical seizure is characterized by sudden changes in the morphology of EEG, but some abnormality in EEG patterns may occur due to different conditions. It is not easy to detect the changes in brain rhythms because of small amplitudes, minute variations and waveforms from the scalp EEG. Moreover, the conventional methods of detection or prediction include visual scanning of EEG signals that is very tedious, time consuming and may be inaccurate. Hence, it is indispensable to obtain correct diagnosis for the treatment of epilepsy after analysing the EEG signals using consistent processing method⁷. Thus a model is proposed to make the detection and prediction using EEG signals that also involves comparison by the use of Support Vector Machine (SVM), Radial Basis Function (RBF) and Neural Network.

In the literature, various methods have been employed to classify these signals using various machine learning algorithms such as neural networks, fuzzy inference system, wavelets, statistical methods and many other⁸⁻¹¹. Authors in¹² used the empirical model decomposition (EMD) to develop a methodology and used SVM for detection of epileptic seizure whereas, authors in¹³ used a cascade of wavelet-approximate entropy to develop a model for feature extraction in the epileptic EEG signal classification. Authors in¹⁴ designed a method based on the EMD for the classification of ictal and seizure-free EEG signals. Authors in¹⁵ have done a quantitative research using power spectral density method to compare classifier in order to determinate which of them has highest rates of classification.

The objective of present work is to develop a computer aided classification system that can automatically diagnose the epilepsy using EEG signals. To come up with the optimal diagnostic system various classifiers are used and their performances are analysed in terms of performance metrics.

The contribution of the present research work is to find out the best classification system using the derived features characterizing the EEG signals. The use of restricted number of features and 10-fold cross-validation make proposed classification system easy to implement and reliable. Authors have worked on various classifiers in¹⁶, and in the present paper, the work is extended by exploring the ability of various classifiers for designing optimal CAD (computer aided classification) systems to model and classify EEG signals. The apparent potential of Neural networks, Support Vector machine, K-Nearest neighbour, Radial Basis function is exploited to propose a generative classifier. Our proposed CAD diagnosis system is completely automated that will help the clinicians in their daily screening of epileptic patients.

METHODOLOGY

Advancement in signal processing and machine learning techniques is making it possible to aid a neurologist by automatically analyse EEG data to detect epileptic patterns.

Analysed Data

In the present work, data used for the research work is made available by University of Bonn, Germany and is in public domain¹⁷. The data used has recordings of 100 single-channel EEG signals of 23.6 s duration. Signals were recorded with 128-channel amplifier system, digitized using 12 bit resolution and sampled at a sampling rate of 173.61Hz. The data set comprises the signals of set Z (as normal condition), set F (as inter-ictal condition) and signals in set S (exhibiting seizure activity) are chosen for this work. Exemplary EEGs of each class are depicted in Fig.2. Several pre-processing steps are to be carried out in order to reduce noise and artifacts and a notch filter is required to eliminate interference induced by external power mains and equipment. The values of the attributes are standardized by normalizing by max-min approach.

Methods

The purpose of this research work is to identify the features of the EEG signals pertaining to epileptic disorder and to construct a computer aided diagnostic system that uses EEG features to accurately classify seizure activity. To analyze and classify the EEG signals with enhanced accuracy and precision various computational techniques are employed which possess the quality of generalization and good predictive power¹⁸. Main objective of this research work is to come up with the best possible classifier exhibiting these properties, so different

classifiers that are already used in literature are compared with respect to their performances. All the statistical features are collected and a feature vector is constituted that is used by the entire above mentioned machine learning algorithms. A detail description of the proposed algorithms is discussed in the following section.

Feature Extraction and Selection

To extract a suitable feature set from the epileptic EEG signals is a challenging task as these features are of prime importance for classification. Any successful diagnostic system based on classification requires a feature set which is unrelated, informative and best representation of the signals. This work has considered statistical features, mean, standard deviation, maximum, energy, entropy, skewness and kurtosis. These features are calculated from each set of every class to achieve representative characteristics of the original signals¹⁹. One of the features for all the three classes is depicted in Fig 3. The features from all the 100 signals of one class are framed together, and similar technique is applied for all the three hundred case. Thus a final feature set is constituted after using features ranking methods and are arranged according to their clinical significance. The ANOVA demonstrated the use of different features by obtaining the p-value less than 0.005. This feature set is used as input to the classifier using machine learning algorithm, and training and testing sets

Table 1a: Summary of active networks (S-F)

| Index | Net. name | Training performance | Test performance | Validation performance | Hidden activation | Output activation |
|-------|------------|----------------------|------------------|------------------------|-------------------|-------------------|
| 1 | MLP 13-5-2 | 96.428 | 100.000 | 96.666 | Identity | Softmax |
| 2 | MLP 13-7-2 | 97.857 | 100.000 | 96.666 | Identity | Softmax |
| 3 | MLP 13-9-2 | 100.000 | 100.000 | 99.666 | Identity | Softmax |

Table 1b: Summary of active networks (S-Z)

| Index | Net. name | Training performance | Test performance | Validation performance | Hidden activation | Output activation |
|-------|-------------|----------------------|------------------|------------------------|-------------------|-------------------|
| 1 | MLP 13-16-2 | 99.000 | 100.000 | 99.000 | Logistic | Softmax |
| 2 | MLP 13-7-2 | 100.000 | 100.000 | 100.000 | Identity | Softmax |
| 3 | MLP 13-5-2 | 98.000 | 99.000 | 99.000 | Exponential | Softmax |

are generated. 10-fold cross-validation technique is employed to reduce any bias of training and test data²⁰. These methods reduce the complexity of the system without affecting the classification performance.

Classification

Various classifiers used for diagnostic system are briefed in this section. The feature vector framed out of all the features of different type of signals is given as input to the classifiers. Based on various performance indices, the performance of classifiers are evaluated for this particular problem. As the main objective of this work is to find out the classifier that best suits this research problem, different classifiers are evaluated after being trained and tested exclusively for each type of signal.

Table 2: Confusion matrix for both the cases

| | Predicted category | |
|--------------|--------------------|------------|
| | Category F | Category S |
| MLP 13-9-2-F | 96 | 1 |
| MLP 13-9-2-S | 0 | 98 |
| | Category S | Category Z |
| MLP 13-7-2-S | 100 | 0 |
| MLP 13-7-2-Z | 0 | 100 |

Artificial Neural Network (ANN) Classifier

ANNs are non linear classifiers that are arranged in three layers viz., input, hidden and output layer. These networks simulate the biological neuron and are capable of performing computational tasks²¹. The number of neurons in the input layer denotes the number of features selected and, number of outputs denotes the number of classes to be classified. The large the number of neurons in hidden layer, more is the complexity. Artificial network adapts itself by sequential training algorithm and its architecture.

Support Vector Machine (SVM) Classifier

SVM is a machine learning algorithm and is most popular algorithm used for classification that uses a hyper plane to separate the data by optimizing the margin between two classes. SVM tries to represent the feature points in space which are mapped in a way that different categories can be divided by a boundary by a clear gap that is as wide as possible. For non linear problems, SVM have ability to learn with different kernel function for classification by changing the different kernel function, as linear, polynomial, radial basis function²². The hyper plane maximizes the margin that is the distance between the hyper plane and the nearest points from each class that are called as support vectors.

Table 3 a): Overall performance for SVM classifier with radial basis kernel function for Case I

| Class Name | Classification summary (S-F) | | | | |
|------------|---|---------|-----------|------------|--------------|
| | Kernel: Radial Basis Function (gamma=0.077) | | | | |
| | Total | Correct | Incorrect | Correct(%) | Incorrect(%) |
| F | 100 | 100 | 0 | 100.00 | 0.0000 |
| S | 100 | 97 | 4 | 97.00 | 3.0000 |

Table 3 b) : Overall performance for SVM classifier with radial basis kernel function for Case II

| Class Name | Classification summary (Z_S) | | | | |
|------------|---|---------|-----------|------------|--------------|
| | Kernel: Radial Basis Function (gamma=0.077) | | | | |
| | Total | Correct | Incorrect | Correct(%) | Incorrect(%) |
| S | 100 | 100 | 0 | 100.0000 | 0.00 |
| Z | 100 | 100 | 0 | 100.0000 | 0.00 |

Radial Basis Function (RBF) Classifier

The design of a neural network can also be perceived as a curve-fitting (approximation) problem in a high-dimensional space. The multidimensional surface is found to represent a best fit to the training data that is further used to interpolate the test data. This network consists of three layers: nonlinear input layer to connect the network to the environment, hidden layer of high dimensionality and the linear output layer that produces the response. Dimension of the hidden space in an RBF network is made high by applying nonlinear transformation prior to a linear transformation²³

Performance Evaluation

For evaluating the performance of a classifier and validate the performance of the proposed method an appropriate criterion is an important concern to make correct predictions. In this paper, the performance of the proposed method is assessed by calculating classification accuracy, confusion matrix, evaluating performance of the classifier in terms of training, testing and validating performances and by plotting receiver operating characteristic (ROC) curve. The exhaustive description of these performance evaluation measures are available in references²⁴

Table 4 a) : Overall performance for SVM classifier with polynomial kernel function for Case I

| Class Name | Classification summary (S-F) Kernel: Polynomial (degree=3.000, gamma=0.077) | | | | |
|------------|--|---------|-----------|------------|--------------|
| | Total | Correct | Incorrect | Correct(%) | Incorrect(%) |
| F | 100 | 100 | 0 | 100.000 | 0.000 |
| S | 100 | 96 | 1 | 96.000 | 4.000 |

Table 4 b) : Overall performance for SVM classifier with polynomial kernel function for Case II

| Class Name | Classification summary (Z_S) Kernel: Polynomial (degree=3.000, gamma=0.077) | | | | |
|------------|--|---------|-----------|------------|--------------|
| | Total | Correct | Incorrect | Correct(%) | Incorrect(%) |
| S | 100 | 100 | 0 | 100.00 | 0.000 |
| Z | 100 | 91 | 9 | 91.00 | 9.000 |

Table 5 a): Summary of active networks with RBF networks

| Index | Net. name | Training perf. | Test . perf | Validation perf. | Hidden activation | Output activation |
|-------|-------------|----------------|-------------|------------------|-------------------|-------------------|
| 1 | RBF 13-5-2 | 92.14286 | 96.6667 | 86.66667 | Gaussian | Identity |
| 2 | RBF 13-5-2 | 93.57143 | 100.0000 | 93.33333 | Gaussian | Identity |
| 5 | RBF 13-30-2 | 92.85714 | 100.0000 | 86.66667 | Gaussian | Softmax |

Table 5 b): Confusion matrix for Case I

| Predicted category | Inter ictal (f) | Ictal (s) |
|--------------------|-----------------|-----------|
| Inter ictal (f) | 91 | 2 |
| Ictal (s) | 9 | 98 |

Table 5 c): Confusion matrix for Case II

| Predicted category | Normal (z) | Ictal (s) |
|--------------------|------------|-----------|
| Normal (z) | 95 | 4 |
| Ictal (s) | 5 | 96 |

RESULTS AND DISCUSSION

In this Section, the proposed methodology is applied on the available database as discussed Section 2. The technique is employed to classify two-class EEG signals from datasets for two cases Case I : Set F vs Set S and Case II: Set S vs Set Z. We experimented with five classifications, namely Artificial Neural Network, Radial Basis Function, and Support Vector Machine (SVM) with different kernels functions. The features are ranked using

SPSS software and technique is implemented using MATLAB.

The classification system consist of three layers of artificial NN with tan-hyperbolic and softmax function as the activation function for hidden and output layers respectively with Cross Entropy as error function and BFGS (Broyden-Fletcher-Goldfarb-Shanno) as the technique used for training neural network²⁵. To avoid over fitting during training of the network , 70% of the data set is employed for training,

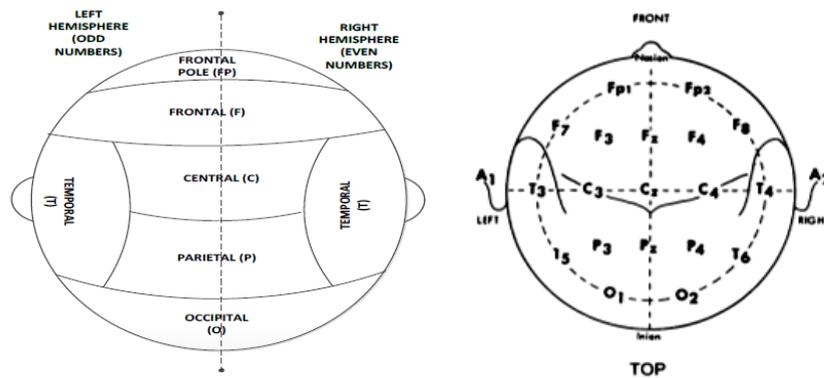


Fig. 1: Electrode placement on the skull with reference to 10-20 International system

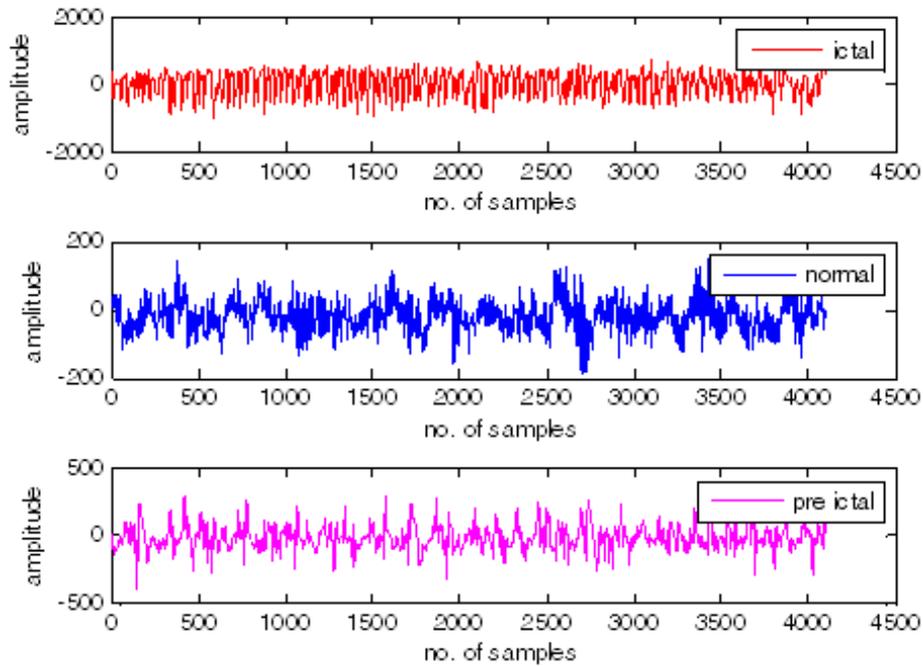


Fig. 2: Exemplary EEGs of each class

15% of the data set for testing and 15% for validation. Such random sampling has been performed 10 times and best 3 independent models have been created for case I and case II as depicted in Table 1a) and 1 b). It is observed in this table that the MLPNN model with 9 nodes in the hidden layer is the better choice for case I giving 99.66% validation performance and for case II to differentiate between class S and class Z, hidden layer with seven nodes gives 100% accuracy. Table 2 depicts the confusion matrix for the best MLPNN model chosen for both cases from which can calculate sensitivity specificity, false rate and classification accuracy.

For this research work, the other classifier used was Support Vector Machine (SVM). The

performance of SVM is based on various kernel functions employed. We have chosen three kernel functions to make our research work more generalized linear, polynomial and radial basis[26]. Number of SVs are calculated with particular value of gamma and henceforth classification summary is tabulated in Table 3 a) and b) for radial basis function kernel and Table 4 a) and b) for polynomial function respectively.

It is observed from the above tables 3 and table 4 that SVM with radial basis function gives the 100% accuracy for classification between ictal and normal candidate whereas 97% accuracy is achieved for classifying ictal and inter-ictal cases. It is also observed that higher rate of classification

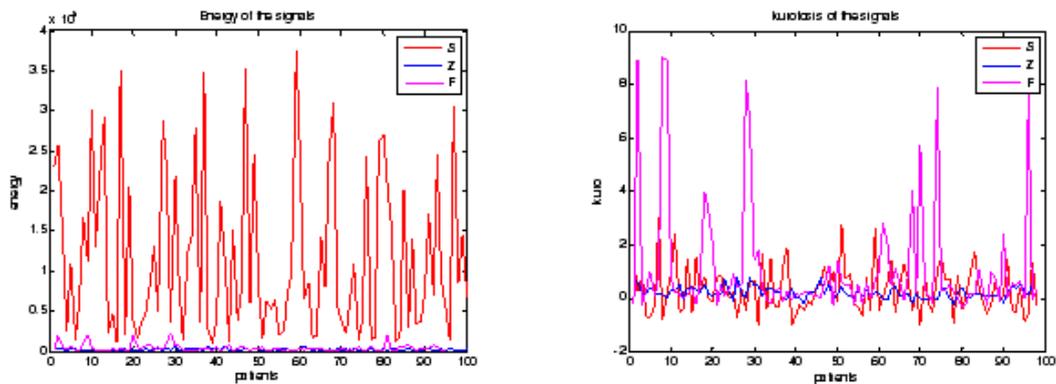


Fig. 3: Depiction of two features: Energy and kurtosis of ictal(S), inter-ictal(F) and normal(Z) signals

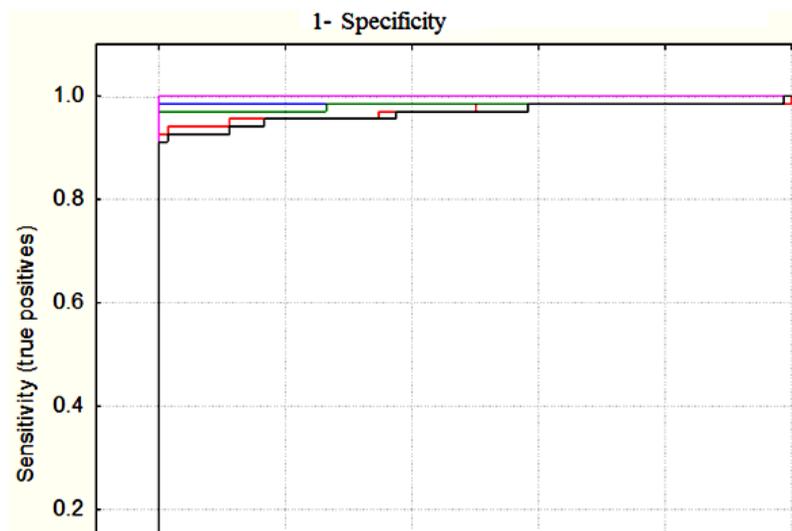


Fig. 4: ROC curve for the proposed classifier

accuracy is achieved for ictal and normal cases as compared to the classification of case II i.e ictal and inter ictal cases.

The third category of classifiers used for this research work is radial basis function as it was inferred from the previous experimentation that SVM gave the best results with RBF kernel. Again, various models were experimented with the dataset and the best three models depicting good classification results are reported. Table 5 a) shows the performance of the models in terms of training, testing and validating for classification. Table 5 b) and 5 c) gives the confusion matrix for both the cases. After reviewing the results, it is observed that classification accuracy is better for differentiating ictal and normal condition as compared to ictal and inter ictal state, following the same trend as for other classifiers.

Finally, to substantiate the classification results ROC curves were plotted for all the models and it was seen that maximum area under curve was found to be of ANN that substantiate our

experimentation for this research problem. Fig 4 represents the ROC curve for this work.

CONCLUSION

The proposed methodology is a step towards modelling the epilepsy prediction as a classification task for two different classes: ictal and normal state and ictal and inter ictal state.. To come up with better model showing highest classification accuracy and good sensitivity and specificity five different classification algorithms were used to classify normal and abnormal patients. Analysing the results comparatively it can be inferred that out of all the tested models MLPNN gave the best results in terms of CA, confusion matrix and misclassification rate followed by SVM with RBF kernel. Lower classification for the same architecture is given by SVM with linear kernel and polynomial kernel. MLPNN does not require feature space dimensionality reduction and is less prone to over fitting and obtain good generalization performance. The results obtained from this research work shows that the MLPNN model has potential in designing EEG based diagnostic system.

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