International Journal of Applied Engineering Research ISSN 0973-4562 Volume 11, Number 1 (2016) pp 120-129

An Empirical Analysis of Different Machine Learning Techniques for Classification of EEG Signal to Detect Epileptic Seizure

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Abstract
Electroencephalogram (EEG) signal is a modest measure of electric flow in a human brain. It is responsible for information flow through the neurons in the brain which controls and monitors the full torso. Hence, to widening and in-depth understanding of effectiveness in EEG signal analysis is the primary focus of this paper. Moreover, machine learning techniques often proven as more efficacious compared to other techniques. To this effect, the present study primarily focuses on the analysis of EEG signal through the classification of the processed data by discrete wavelet transform (DWT) for identification of epileptic seizures using machine learning techniques. Machine learning techniques like neural networks and support vector machine (SVM) are the focus of this paper for classification of EEG signals to label epilepsy patients. In neural networks, the empirical analysis gives focus on multi-layer perceptron, probabilistic neural network, radial basis function neural networks, and recurrent neural networks. Further, for multi-layer neural networks different propagation training algorithms are examined such as Back-Propagation, Resilient-Propagation, and Quick-Propagation. For SVM, several kernel methods are considered such as Linear, Polynomial, and RBF for empirical analysis. The analysis confirms with the present setting that, recurrent neural network performs poor in all the cases of prepared epilepsy data. However, SVM and probabilistic neural networks are quite effective and competitive.

Keywords: EEG Signal, Epilepsy, Classification, Machine Learning

Introduction

Epilepsy is a chronic disorder of mental ability that has an abnormal EEG signal flow [1], which manifests in the disoriented human behaviour. Around 40 to 50 million people in this world are affected by this disease [2]. People also call it as fits that causes loss of memory and disruption in consciousness, strange sensations, and significant alteration in emotions and behaviour. Research work related to epilepsy has mainly tried to differentiate between Ictal (seizure period) and Interictal (period between seizures) EEG signal. So the transition from preictal to ictal state for an epileptic seizure consists of a gradual change from chaotic to ordered wave forms. However, the amplitude of the spikes does not necessarily represent the severity of seizures [2].

The differentiation between seizure and the common artefact is easy to recognize. Generally, seizures within EEG measurement [3] have a prominent spiky, repetitive, transient, or noise-like pattern. So, unlike other general signals, EEG signal is very difficult to understand and analyse for an untrained observer. These signals are recorded with the help of a set of electrodes placed on the scalp using 10 to 20 electrode placement systems. In this system, the electrodes are placed with specific name according to specific parts of the brain, for example Frontal Lobe (F), Temporal Lobe (T), etc. These naming and placement schemes are described in [3].

There are also several neuro-imaging techniques such as functional magnetic resonance imaging (fMRI) and position emission tomography (PET) facilitate the diagnosis of epilepsy more effectively. An epileptic seizure can be characterized by paroxysmal occurrence of synchronous oscillation. These impressions can be separated into two categories depending on the extent of involvement in different brain regions such as focal or partial and generalized seizures [4]. Focal seizure also known as epileptic foci are generated at specific sphere in the brain. In contrast, generalized seizures occur in most parts of the brain. A careful analysis and diagnosis of EEG signals to detect epileptic seizure in the human brain can contribute a substantial insight and support to medical science. The EEG is beneficial as well as a cost effective way for the study of epilepsy. For generalized seizure, the duration of seizure can be easily detected by naked eyes. But it is very difficult to recognize intervals during focal epilepsy.

To properly detect epileptic seizures in EEG signal, classification is the most effective and useful technique [5]. Classification is a data mining technique used for pattern recognition [6]. It is used to predict group membership for unknown data instances. By designing a classifier model using different machine learning approaches, we can identify epileptic seizures in EEG brain signal. Before classification of raw EEG signal, pre-processing is necessary to get it into a proper feature set format. Generally, the data sample of EEG is not linearly separable. Thus, to obtain non-linear discriminating function for classification, we are using machine learning techniques. Moreover, the case of limiting our focus on machine learning approaches is their capability and efficiency for smooth approximation and pattern recognition.

In this analytical study, we have considered publicly available EEG dataset related to epilepsy for all experimental evaluations. Based on this, there are mainly two phases of the epileptic seizure detection process that are carried out. The first phase is to analyse EEG signal and convert it to a set of samples with a set of features. The second phase is to classify already processed data into different classes such as epilepsy or normal.

The rest of the sub-divisions of this paper are organized as follows. Section 2, describes the recording and analysis of EEG dataset. Signal decomposition and different classification methods based on machine learning techniques are described in Section 3. Section 4, passes on the detail of empirical work and analysis of results obtained by different machine learning models. Section 5, draws the conclusions and suggests possibilities for future work.

Data Description and Preparation

In the present work, we have collected data from [7] which is a publicly available database [8] related to diagnosis of epilepsy. This resource provides five sets of EEG signals. Each set contains reading of 100 single channel EEG segments of 23.6 seconds duration each. These five sets are described as follows. Data sets A and B are considered from five healthy subjects using a standardized electrode placement system. Set A contains signals from subjects in a slowed down state with eyes open. Set B also contains signal same as A but ones with the eyes closed. The data sets C, D and E are recorded from epileptic subjects through intracranial electrodes for interictal and ictal epileptic activities. Set D contains segments recorded from within the epileptogenic zone during seizure free interval. Set C also contains segments recorded during a seizure free interval from the hippocampal formation of the opposite hemisphere of the brain. Set E only contains segments that are recorded during seizure activity. All signals are recorded through the 128 channel amplifier system. Each set contains 100 single channel EEG data. In all there are 500 different single channel EEG data. In the next section we will illustrate how to crack these signals using discrete wavelet transform [9] and prepare several statistical features and form a proper sample feature dataset.

A. Wavelet Transform

This is a modern signal analysis technique which overcomes the limitations of other transformation techniques. Other transformation methods may include Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT), etc. The major restrictions of these techniques are the analysis limits to stationary signals. These are not effective for analysis of transient signals such as EEG signal. Transient in the sense the frequency is changing rapidly with respect to time. Then, with the help of wavelet coefficients [10] we can analyse transient signals easily and also efficiently. Wavelet transform can be of two types: Continuous Wavelet Transform (CWT) [11] and Discrete Wavelet Transform (DWT) [12-13].

i. Continuous Wavelet Transform

It is defined as in equation (1):

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t).\overset{\nabla}{\varphi}_{a,b}(t)dt \qquad (1)$$

Where, x(t) represents the original signal, a and b represents the scaling factor and translation along the time axis, respectively. The ∇ symbol denotes the complex conjugation and $\overset{\nabla}{\varphi}_{a,b}$ is computed by scaling the wavelet at time band scale a (as shown in equation (2)).

$$\overset{\nabla}{\varphi}_{a,b}(t) = \frac{1}{\sqrt{|a|}}\varphi\left(\frac{t-b}{a}\right) \qquad (2)$$

Where, $\overset{\nabla}{\varphi}_{a,b}(t)$ stands for the mother wavelet. In CWT, it is presumed that the scaling and translation parameters a, and b changes continuously. But the main disadvantage of CWT is that the calculation of wavelet coefficients for every possible scale can result in a large amount of data. It can surmount with the help of DWT.

ii. Discrete Wavelet Transform

It is almost same as CWT except that the value of a andb does not change continuously. It can be defined as (shown in equation (3)):

$$DWT = \frac{1}{\sqrt{|2^p|}}\int_{-\infty}^{\infty} x(t)\varphi\left(\frac{t-2^p q}{2^p}\right)dt \qquad (3)$$

Where a and b of CWT are replaced in DWT by 2^p&2^q respectively.

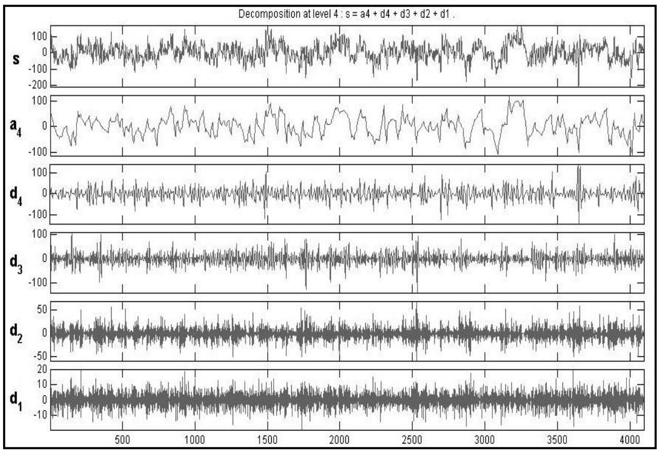

Figure 1: Single channel EEG signal decomposition of set A using db-2 up to level 4

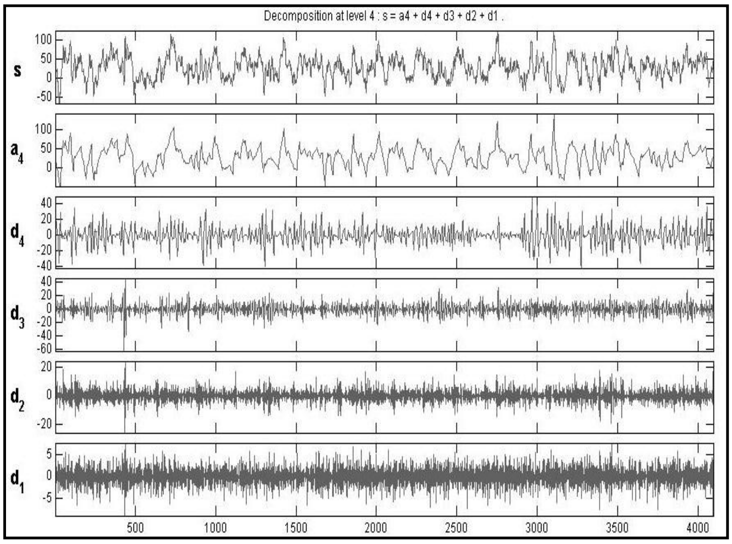

Figure 2: Single channel EEG signal decomposition of set D using db-2 up to level 4

It is a transformation technique that provides a new data representation which can spread to multiple scales. Therefore, the analysis of transforming signal can be performed at a multiple resolution scale. DWT is performed by successively passing the signal through a series of high pass and low pass filters producing a set of detail and approximation coefficients. This generates a decomposing tree known as Mallat's decomposition tree. In this analytical work, the raw EEG signals that have been picked up from web resources is decomposed using DWT [13] available as a toolbox in MATLAB. This signal is decomposed using the Daubechis Wavelet function of order 2 up to 4 levels [12]. Thus, it produces a series of wavelet coefficient like four detailed coefficients (D1, D2, D3, and D4) and an approximation signal (A4). Figs. 1, 2, and 3 provides a snapshot of this decomposition of a single channel EEG recording from set A, D, and E respectively.

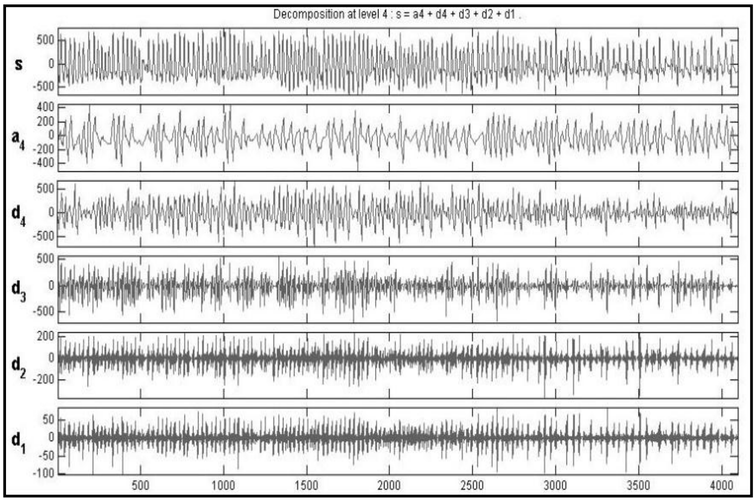

Figure 3: Single channel EEG signal decomposition of set E using db-2 up to level 4

Later, on this decomposition some of the statistical features of many have been extracted from the signals such as Minimum (MIN), Maximum (MAX), MEAN, and Standard Deviation (SD). Fig. 4, is a sample output of the MATLAB toolbox showing different features of a single channel EEG recording from set A and set E. The same procedure can be followed for all other EEG recordings to make a perfect set. So, after this level, we are ready with a sample feature dataset of order 500 by 20 matrixes as shown in Table 1. Then it can be further used for classification tasks.

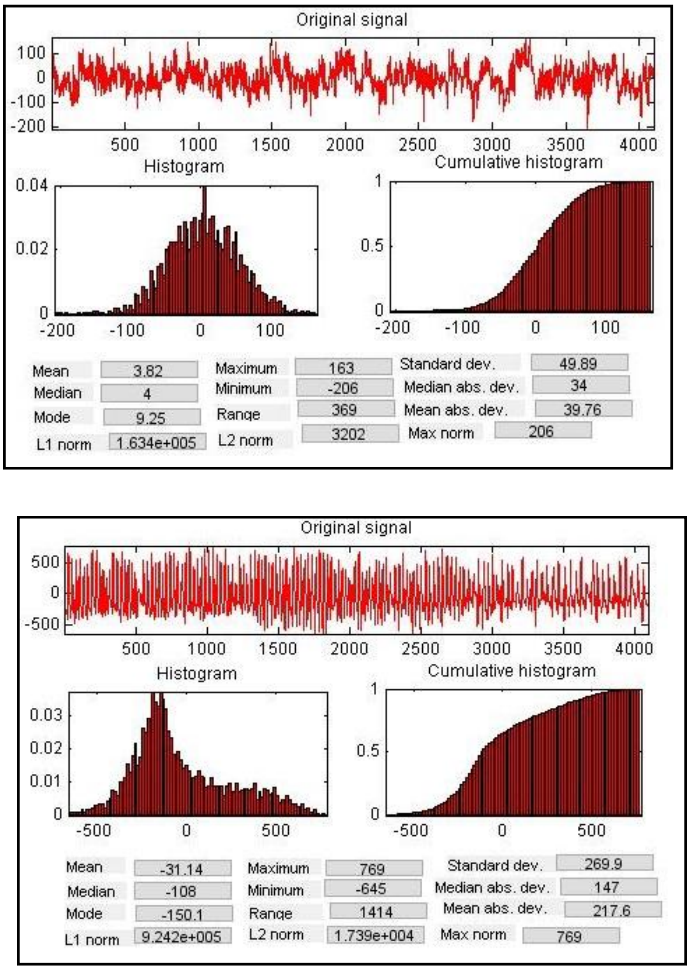

Figure 4: Statistical features extraction from signals after decomposition

Table 1: Structure and dimension of dataset for EEG signal classification

Seizure Detection Sets	Size of sample	Class 0	Class 1
Set1- (A & E)	200 x 20	100 x 20	100 x 20
Set 2- (D & E)	200 x 20	100 x 20	100 x 20
Set 3- (A+D & E)	300 x 20	200 x 20	100 x 20

Except DWT, there are other feature extraction techniques [5] that can also be used successfully to extract features from the raw EEG signal. These techniques may include Wavelet Packet Decomposition (WPD), Principal Component Analysis (PCA), Lyapunov Exponent, ANOVA test, etc.

Machine Learning Classifiers

Machine learning (ML) is a set of computerized techniques, which focus to automatically learn to recognize complex patterns and make intelligent decisions based on data. ML has proven its ability to uncover hidden information present in large complex datasets. Using ML, it is possible to cluster similar data, classify, or to find association among various features [14-15]. In the context of EEG signal analysis, ML is the application of algorithms to extracting patterns from EEG signals [16]. However, there are other steps that are also carried out e.g., data cleaning & pre-processing, data reduction & projection, incorporation of prior knowledge, proper validation and interpretation of results while analysing EEG signals. EEG analysis has number of challenges which make it suitable for machine learning techniques [17].

- EEG comes in large databases.
- EEG recordings are very noisy.
- EEG signals have large temporal variance.

Some of the popular machine learning approaches is neural networks, evolutionary algorithms, fuzzy theory, and probabilistic learning. In this analytical work, our focus is restricted with neural networks, support vector machines, and probabilistic neural networks for classification EEG signals.

A. Multilayer Perceptron Neural Network (MLPNN)

Artificial neural network simulates the operation of a neural network of the human brain and solves a problem. Generally, single layer Perceptron neural networks are sufficient for solving linear problems, but nowadays the most commonly employed technique for solving nonlinear problems is Multilayer Perceptron Neural Network (MLPNN) [18]. It can hold various layers such as one input and one output layer along with at least one hidden layer. There are connections between different layers for data transmission. The connections are generally weighted edges to add some extra information's to the data and it can be propagated through different activation functions.

The heart of designing an MLPNN is the training of network for learning the behaviour of input-output patterns. In this work, we have designed an MLPNN with the help of a Java Encog framework. This network is trained with the help of three popular training algorithms such as Back- propagation (BP) [19], Resilient Propagation (RPROP) [20], and Manhattan Update Rule (MUR).

Back-propagation training algorithm [21-23] is different from other algorithms in terms of the weight updating strategies. In back propagation [24-26], generally weight is updated by the equation (4) [27-29].

$$w_{ij}(k+1) = w_{ij}(k) + \Delta w_{ij}(k) \tag{4}$$

Where in regular gradient decent by equation (5),

$$\Delta w_{ij}(k) = -\eta \frac{\partial E}{\partial w_{ij}}(k) \tag{5}$$

With a momentum term by equation (6),

$$\Delta w_{ij}(k) = -\eta \frac{\partial E}{\partial w_{ij}}(k) + \mu \Delta w_{ij}(k-1) \tag{6}$$

Resilient propagation [20] is a supervised training algorithm for feed forward neural network. Instead of magnitude, it takes into account only the sign of the partial derivative, or gradient decent and acts independently on each weight. The advantage of RPROP algorithm is that it needs no setting of parameters before applying it. The weight updating is done according to the equation (7) and equation (8) . Equation 4, is same for the RPROP for weight update.

$$\Delta w_{ij} = \begin{cases} +\Delta_{ij}, if \frac{\partial E}{\partial w_{ij}}(k) > 0, \\ +\Delta_{ij}, if \frac{\partial E}{\partial w_{ij}}(k) < 0, \\ \quad 0, Otherwise \end{cases} \tag{7}$$

$$\Delta_{ij} = \begin{cases} \eta_+ * \Delta_{ij}(k-1), S_{ij} > 0, \\ \eta_- * \Delta_{ij}(k-1), S_{ij} < 0, \\ \Delta_{ij}(k-1), Otherwise \end{cases} \tag{8}$$

Where, $S_{ij} = \frac{\partial E}{\partial w_{ij}}(k-1) * \frac{\partial E}{\partial w_{ij}}(k)$ and $\eta_+ = 1.2$and $\eta_- = 0.5$.

Manhattan update rule also works similar to RPROP and only uses the sign of the gradient whereas magnitude is discarded. If the magnitude is zero, then no change is made to the weight or threshold value. If the sign is positive, then the weight or threshold value is increased by a specific amount defined by a constant. If the sign is negative, then the weight or the threshold value decreases by a specific amount defined by a constant. This constant must be provided to the training algorithm as a parameter.

B. Support Vector Machine (SVM)

SVM is the most widely used machine learning technique based pattern classification technique nowadays. It is based on statistical learning theory and was developed by Vapnik in the year 1995. The primary aim of this technique is to project nonlinear separable samples onto another higher dimensional space by using different types of kernel functions. In late years, kernel methods have received major attention, especially due to the increased popularity of Support Vector Machines [30]. Kernel functions play a significant role in SVM [31] to bridge from linearity to nonlinearity. Least square SVM [32] is also an important SVM technique that can be applied for classification task [33]. Extreme learning Machine and Fuzzy SVM [34-36] and Genetic algorithm tuned expert model [34] can also be applied for the purpose of classification.

In this analytical work, we have evaluated three different types of kernel functions [37], i.e. Linear, Polynomial, and RBF kernel [38]. Linear kernel is the simplest kernel function available. Kernel algorithm using a linear kernel is often

equivalent to their non-kernel counterparts [39]. From the result table, it can be clearly understood that for a classification problem consisting of only sets A & E or D & E, it is providing 100% accuracy. But it is not able to classify properly for sets A+D & E.
Polynomial kernel is a non-stationary kernel. This kernel function can be represented as given in equation (9).

$$K(x, y) = (\alpha x^T y + c)^d \quad (9)$$

Where, α, c and d denotes slope, any constant, and degree of polynomial, respectively.
Somehow this kernel function [40-41] is better as compared to linear kernel function. However, the RBF kernel function [42] has been proven as the best kernel function used for this application, which can classify different groups with 100% accuracy with a minimum time interval.

C. Variants of Neural Network (PNN, RNN, RBFNN)

This paper also includes some experimental evaluations for other types of neural networks. Other than MLPNN, there are many different types of neural networks have been developed over the year for solving problems with varying complexities of pattern classification. Some of these includes: Recurrent Neural Network (RNN) [43], Probabilistic Neural Network (PNN) [44], and Radial Basis Function Neural Network (RBFNN) [45]. Also, we have used Resilient Propagation & Back propagation for training of networks wherever they are required.

i. Recurrent Neural Network

RNN [46] is a special type of artificial neural network having a fundamental feature i.e. the network contains at least one feedback connection [47], so that activation can flow round in a loop. This feature enables the network to do temporal processing and learn the patterns. The most important common features shared by all types of RNN [48-49] are: they incorporate some form of Multilayer Perceptron as sub-system; they implement the non-linear capability of MLPNN [50-51] with some form of memory. In this research work the ANN architecture, we have implemented for modelling and classifying is the Elman Recurrent Neural Network (ERNN). It was originally developed by Jeffrey Elman in 1990. The Back-Propagation Through Time (BPTT) learning algorithm is used for training [52-53], which is an extension of Back-propagation that performs gradient decent on a complete unfolded network.If a network training sequence starts on time t_0 and ends at time t_1, the total cost function can be calculated as (shown in equation (10):

$$\mathrm{E_{total}}(\mathrm{t_0}, \mathrm{t_1}) = \sum_{\mathrm{t=t_0}}^{\mathrm{t_1}} \mathrm{E}_{\frac{\mathrm{sse}}{\mathrm{ce}}}(\mathrm{t}) \quad (10)$$

And the gradient decent weight update can be calculated as (shown in equation (11)):

$$\Delta w_{ij} = -\eta \sum_{t=t_0}^{t_1} \frac{\partial E_{\frac{sse}{ce}}(t)}{\partial w_{ij}} \quad (11)$$

ii. Probabilistic Neural Network

PNN was first proposed by Specht in 1990. It is a classifier that maps input patterns in a number of class levels. It can be forced into a more general function approximator. This network is organized into a multilayer feed forward network with input layer, pattern layer, summation layer, and the output layer. PNN [50] is an implementation of a statistical algorithm called Kernel Discriminant Analysis. The advantages of PNN are: it has a faster training process as compared to Back-Propagation. Also, there are no local minima issues. It has a guaranteed coverage to an optimal classifier as the size of the training set increases. But it has few disadvantages like slow execution of the network because of several layers and heavy memory requirements, etc.

In PNN [54] a Probability Distribution Function (PDF) is computed for each population. An unknown sample *s* belongs to a class *p* if (as shown in equation (12)),

$$PDF_p(s) > PDF_q(s) \forall p \neq q \quad (12)$$

Where, $\mathrm{PDF_k(s)}$ is the PDF for class k.

Other parameters used are Prior Probability- h, Misclassification Cost – c, so the classification decision becomes (as shown in equation (13)),

$$h_p c_p PDF_p(s) > h_q c_q PDF_q(s) \forall p \neq q \quad (13)$$

PDF for a single sample can be calculated by using the formula (as shown in equation (14)),

$$PDF_k(s) = \frac{1}{\sigma} W\left(\frac{s - s_k}{\sigma}\right) \quad (14)$$

Where s – Input (unknown), $\mathrm{s_k}$ - kth Sample, W - Weighting Function, σ - Smoothing parameter.PDF for a single population can be calculated by taking the average of PDF of n samples (as shown in equation (15)).

$$\mathrm{PDF_k^n(s)} = \frac{1}{\mathrm{n}\sigma} \sum_1^{\mathrm{n}} \mathrm{W}\left(\frac{\mathrm{s - s_k}}{\sigma}\right) \quad (15)$$

From the result table, it have been experimentally proved that for epilepsy identification in EEG signal PNN gives the most accurate result by taking minimum amount of time.

iii. Radial Basis Function Neural Network

RBF networks are also a type of feed-forward network trained using a supervised training algorithm. The main advantage of RBF network is that it has only one hidden layer. The RBF network, usually trains much faster than back-propagation networks. This kind of network is less susceptible to problems with non-stationary inputs because of the behaviour of radial basis function hidden units. The general formula for the output of RBF network [55] can be represented as follows (as shown in equation (16)), if we consider the Gaussian function as basis function.

$$y(x) = \sum_{i=1}^{M} w_i e^{\left(\frac{-(\|x - c_i\|)^2}{2\sigma^2}\right)} \quad (16)$$

where, x, y(x), $\mathrm{c_i}$, σ, and Mdenotes input, output, center, width, and number of basis function centered at $\mathrm{c_i}$, similarly $\mathrm{w_i}$ denotes weights.

For this work, we have constructed a Radial Basis Function Network by taking the Gaussian function as the basis function and considering randomized centres and width.

Empirical Study

This section gives an empirical study on different classification techniques based on machine learning approach for detection of epilepsy in EEG brain signal. Various experiments are done to validate this empirical study. The Machine Learning based classifiers are proved as the most efficient way for pattern recognition. It aids to design models that can learn from some previous experience (known as training) and further it can be able to recognize appropriate patterns for unknown samples (known as testing).

All experiments for this research work are performed using a powerful Java Framework known as Encog [56] developed by Jeff Heaton and his team. Currently we are using Encog 3.2 Java framework for all experimental result evaluation. This is the latest version and it supports almost all the features of machine learning techniques. Along with this framework, there are a lot of packages, classes and methods that have been defined to support the experimental evaluations. Java is the most potent and efficient language nowadays. The rightness of the experimental works can be verified easily using this language. There are almost nine different machine learning algorithms that have been implemented for EEG signal classification for epileptic seizure detection.

A. Environment and Parameter Setup

The Encog Java framework provides a vast circle of library classes, interfaces and methods that can be utilized for designing different machine learning based classifier models. There are lists of parameters (as shown in table 2) required to be set for smooth execution of models.

Table. 2: List of parameters for models execution

Classification Techniques	**Required Parameters and values**
MLPNN/BP	Activation Function - Sigmoid Learning Rate = 0.7 Momentum Coefficient = 0.8 Input Bias - Yes
MLPNN/RPROP	Activation Function - Sigmoid Learning Rate = NA Momentum Coefficient = NA Input Bias – Yes
MLPNN/MUR	Activation Function - Sigmoid Learning Rate = 0.001 Momentum Coefficient = NA Input Bias - Yes
SVM/Linear	Kernel Type – Linear Penalty Factor = 1.0
SVM/Polynomial	Kernel Type – Polynomial Penalty Factor = 1.0
SVM/RBF	Kernel Type – Radial Basis Function Penalty Factor = 1.0
PNN	Kernel Type – Gaussian Sigma low – 0.0001 (Smoothing Parameter) Sigma high – 10.0 (Smoothing Parameter) Number of Sigma - 10
RNN	Pattern Type – Elman Primary Training Type – Resilient Propagation Secondary Training Type – Simulated Annealing **<u>Parameters for SA</u>** Start Temperature – 10.0 Stop Temperature – 2.0 Number of Cycles - 100
RBFNN	Basis Function – Inverse Multiquadric Center& Spread Selection – Random Training Type– SVD (Singular Value Decomposition)

B. Result and Analysis

Here, we have hashed out about the performance of all machine learning based classifiers for classifying EEG signal. The different measures used for performance estimation are like Specificity (SPE), Sensitivity (SEN), Accuracy (ACC) and Time elapsed for execution of models. From the evaluation result given in table 3 it is clear that MLPNN with resilient propagation is the most efficient training algorithm both in conditions of accuracy as well as the amount of time needed to execute the programs requiring different shapes such as A&E, D&E and A+D & E. This MLPNN technique can be compared with other machine learning techniques.

Table 4, shows a comparison of different Kernel types used for classification using Support Vector Machine (SVM). It is the most powerful and efficient machine learning tool for designing classifier model. This table clearly shows quite a good result for SVM with RBF kernel.

Table 5, defines a list of experiments led by studying different forms of Neural Network, such as Radial Basis Function Neural Network, Probabilistic Neural Network and Recurrent Neural Network. It suggests the effectiveness of using PNN for classification of EEG signal for detecting epileptic seizures.

C. Comparative Analysis

The following table 6, gives a detailed empirical analysis of the performance of different classification techniques based on machine learning approaches.

Table 3: Experimental evaluation result of MLPNN with different training algorithms

Cases for Seizure Types	Multi-Layer Perceptron Neural Network with different Propagation Training Algorithms											
	Back-Propagation				Resilient-Propagation				Manhattan-Update Rule			
	SPE	SEN	ACC	TIME	SPE	SEN	ACC	TIME	SPE	SEN	ACC	TIME
Case1 (A,E)	100	90.09	94.5	16.52	99.009	100	99.5	2.846	97.29	77.77	85	7.541
Case2 (D,E)	100	83.33	90	22.22	99.009	100	99.5	2.547	55.68	78.78	60	7.181
Case3 (A+D,E)	100	86.95	92.5	23.12	95.85	85.98	92.33	14.79	93.78	82.24	89.66	14.85

Table 4: Experimental evaluation result of SVM with different kernel types

Cases for Seizure Types	Support Vector Machine with different Kernel Types											
	Linear				Polynomial				RBF			
	SPE	SEN	ACC	TIME	SPE	SEN	ACC	TIME	SPE	SEN	ACC	TIME
Case1 (A,E)	100	100	100	2.127	100	100	100	2.101	100	100	100	2.002
Case2 (D,E)	100	100	100	1.904	100	100	100	1.902	100	100	100	2.021
Case3 (A+D,E)	90.67	76.63	85.66	11.61	100	99.009	99.66	7.24	100	100	100	2.511

Table 5: Experimental evaluation result of RBFNN, RNN, PNN with different training algorithms

Cases for Seizure Types	Other Types of Neural Network											
	RBF Neural Network				Probabilistic Neural Network				Recurrent Neural Network			
	SPE	SEN	ACC	TIME	SPE	SEN	ACC	TIME	SPE	SEN	ACC	TIME
Case1 (A,E)	83.076	65.925	71.5	2.051	100	100	100	0.967	77.173	73.148	75	10.31
Case2 (D,E)	100	97.08	98.5	1.828	100	100	100	0.977	64.705	71.604	67.5	13.29
Case3 (A+D,E)	92.30	66.41	81	2.928	100	100	100	1.616	67.346	66.666	67.333	19.58

Table 6: Comparative Analysis of different Machine Learning Classification Techniques

Machine Learning Classification Technique	Case-1 (set A & E)		Case-1 (set D & E)		Case-1 (set A+D & E)	
	Overall Accuracy in %age	Approximate Time taken in seconds	Overall Accuracy in %age	Approximate Time taken in seconds	Overall Accuracy in %age	Approximate Time taken in seconds
MLPNN/BP	94.5	16.527	90	22.226	92.5	23.127
MLPNN/RP	99.5	2.846	99.5	2.547	92.33	14.798
MLPNN/MUR	85	7.541	60	7.181	89.66	14.85
SVM/Linear	100	2.127	100	1.904	85.66	11.61
SVM/Ploy	100	2.101	100	1.902	99.66	7.24
SVM/RBF	100	2.002	100	2.021	100	2.511
PNN	100	0.967	100	0.977	100	1.616
RNN	75	10.31	67.5	13.29	67.33	19.58
RBFNN	71.5	2.051	98.5	1.828	81	2.928

Conclusion

The detection of epileptic seizure in EEG signal can be performed by classifying these signal collected from different patients in different situations. This classification can be accomplished by using different machine learning techniques. In this work, we have compared the functioning and efficiency of different machine learning techniques like MLPNN, RBFNN, RNN, PNN, and SVM for classification of EEG signal for epilepsy identification. Further, the tool MLPNN uses three training algorithms BACKPROP, RPROP, and Manhattan Update Rule. Similarly, SVM uses three kernels such as Linear, Polynomial, and RBF kernels.). This comparative study clearly shows the difference in the efficiency of different algorithms with respect to the task for classification task. From the above experimental study we can conclude that SVM is the most efficient and powerful machine learning technique for classification purpose. Again SVM with RBF kernel provides the maximum accuracy of the classification task. PNN is also a good competitor for SVM for this application. But as compared to SVM, PNN has some extra overhead of setting parameters. Lot of research is still going on to modify some algorithms to increase their efficiency by incorporating some optimization algorithms, like we can also enhance the performance of RBFNN to achieve the required accuracy.

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