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Performance Comparison for MLP Networks Using Various Back Propagation Algorithms in Epileptic Seizure Detection

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Abstract: Epilepsy can be diagnosed using technologies like Electroencephalogram (EEG), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), etc. In this research, researchers inspect EEG signals for seizures. The seizure is recognized with the support of Independent Component Analysis and the ascertained signals are trained under supervision by making use of neural networks technique namely backpropagation algorithm. In the proposal, performance of network is evaluated using publicly available EEG dataset for various backpropagation training functions such as Gradient Descent Algorithm (GD), Scaled Conjugate Gradient (SCG), One Step Secant (OSS), Powell-Beale Restarts (PBR), Gradient Descent with Adaptive (GDWA), Fletcher-Powell Conjugate Gradient (FPCG) and Levenberg Marquardt (LM) Backpropagation are used here for the comparison technique. On comparing the performance of these aforementioned algorithms, highest accuracy with lowest mean square error was obtained for scaled conjugate gradient.

Key words: Epilepsy, independent component analysis, backpropagation algorithms, Gradient Descent algorithm (GD), Scaled Conjugate Gradient (SCG), One Step Secant (OSS), Powell-Beale Restarts (PBR), Gradient Descent with Adaptive (GDWA), Fletcher-Powell Conjugate Gradient (FPCG) and Levenberg Marquardt (LM) backpropagation, epoch, regression

INTRODUCTION

The term epilepsy is a common and disparate set of chronic neurological disorders which encompasses different types of seizures. It is defined by recurring and unprovoked seizures which may produce strange sensations and emotions or behavior in people. Seizures or paroxysms are temporary amendments in brain functions due to atypical electrical activity of a collection of brain cells that present with perceptible clinical symptoms and findings. Epilepsy can be characterized by an unexpected and abrupt malfunction of the brain that is termed as seizure. But seizures may also occur in those people who have not been subjected to epilepsy. The superficial effect of epileptic seizure may be a wild thrashing movement or a mild loss of awareness. These reflect the clinical signs of activities of the neurons such as excessive or hyper synchronous activities (Lehnertz *et al*., 2003). Approximately one in every 100 people will have the possibility of facing seizure at some point in their life (Iasemidis *et al*., 2003). Nearly 4% of people will have experienced unprovoked seizure by the age of 80 and a chance of suffering a second seizure will be between 30 and 50%. Epilepsy and seizure are two disparate terms wherein epilepsy is the causal tendency of the brain to create a sudden rupture of electrical energy and seizures are the symptoms of epilepsy.

Epilepsy can be largely classified into two categories namely idiopathic epilepsy and symptomatic epilepsy. The idiopathic epilepsy is a type of epilepsy in which the cause of the occurrence of epilepsy remains unmarked whereas the symptomatic epilepsy is one in which the concrete cause is identified. The latter is typically identified using any one of the consequent symptoms: serious illness in the nervous system, stroke, severe damage to the skull, etc. Generally seizures are classified into almost twenty types. These categories are further segregated into two types, namely partial and generalized seizures.

Partial seizures also known as focus seizures or localized seizures are later classified into simple partial seizures and complex partial seizures. These seizures affect only a part of the brain where the electrical disturbances are constrained to a precise area of one cerebral hemisphere. The difference between both types is that in simple partial seizures a small part of any one of the lobes will be affected and the person retains consciousness but in a complex partial seizure a larger

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part of the hemisphere is affected than the former and the person may even lose consciousness. If there is a spread of partial seizure from one hemisphere to the other part of the brain this may result in the emergence of a secondarily generalized seizure. Generalized seizures trouble both the cerebral hemispheres from the inception of the seizure. They generate failure of consciousness either for a short duration or for a longer period of time.

Though various technologies are available for the diagnosis of epileptic seizure like Electroencephalogram (EEG), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), etc., the widely used among these is the EEG signals. The incentive for the selection of EEG over the other two technologies is that the EEG signals record umpteen amount of information regarding the function of the brain. Electroencephalography (EEG) is exemplified as the representative signal containing information of the electrical activity generated by the cerebral cortex nerve cells. This has been the most used signal in clinical assessment of brain activities and the detection of epileptic form discharges in the EEG is an important component in the diagnosis of epilepsy (Mohseni *et al*., 2006). The Electroencephalograph (EEG) signals involve a great deal of information about the function of the brain. EEG obtained from scalp electrodes is a superposition of a large number of electrical potentials arising from several sources (including brain cells, i.e., neurons and artifacts) (Ungureanu *et al*., 2004). In spite of the potentials, arising from independent neurons inside the brain rather than their superposition are of keen interest to the researchers and physicians for describing the cerebral activity. Direct measurements from the different locations in the brain which requires surgery is placed with electrodes. Since, this method causes pain and more risk for the subject this is not considered within the acceptable limits. An improved solution would be to calculate the signals of interest from the EEG obtained on the scalp.

Generally signal processing involves analysis, interpretation and manipulation of signals. Signal processing is broadly classified into Analog signal processing and digital signal processing. The spirit of this research is Digital Signal Processing (DPS). DSP represents signals as a series of numbers or symbols and it includes the processing of these symbols with the aid of tremendous digital techniques. DSP is a combination of audio and speech signal processing, sonar and radar signal processing, digital image processing, sensor array processing, spectral estimation, statistical signal processing, signal processing for communications, biomedical signal processing, seismic data processing, etc. Many techniques have been developed to derive information from EEG signals that can be used to develop algorithms for prediction or detection of epileptic seizures such as Wavelet transform (Chen *et al*., 2002) non-linear systems (Casdagli *et al*., 1997), recurrent neural network (Guler *et al*., 2005), logistic regression (Subasia and Ercelebi, 2005), spectral densities of DWT coefficients (Fox *et al*., 1990), etc. Here, by using the Fast ICA, i.e., Fast Independent Component Analysis, a prominent statistical signal processing technique the epileptic seizure in an EEG signal is discovered.

PREVIOUS RESEARCH

Literature presents various related research that are dealing with the detection of epileptic seizure disorders using EEG signals. Among the earlier study a handful of researches make use of the Statistical Signal Processing and Artificial Intelligence (AI) to achieve epileptic seizure detection from EEG signals. Some of the essential contributions are described.

Tzallas *et al*. (2007) have presented a method for EEG signal analysis based on time-frequency analysis. The selected EEG signals are initially examined by making use of Time-Frequency Methods and a number of features responsible for the representation of energy distribution in the time frequency plane are extracted from each and every segment. Consequently the extracted features are given as input to an Artificial Neural Network (ANN) which helps in the provision of supreme classification of segments of EEG on the subject of the existence of seizures or not. In order to perform this classification they made avail of an openly available dataset. The evaluation results were very efficient representing an overall accuracy rate of 97.72-100%.

Gardner *et al*. (2006) have invented an application of one-class Support Vector Machine (SVM) for the purpose of accomplishing seizure detection in humans. The technique which was proposed mapped the time series of intracranial Electroencephalogram (EEG) into equivalent novelty sequences based on the differentiation of short-time, energy-based statistics that were calculated from one-second windows of data. Based on epochs of interictal (normal) EEG a classifier was trained. Along with this a hypothesis test was carried out to determine when the changes in parameter differ significantly from its nominal value, representing a seizure detection event. On the motive of reducing the false alarm rate of the system, outputs were gated using persistence in a one-shot manner. The novelty detection paradigm conquered three important setbacks of its competitors. The necessity for collection of seizure data, exactly mark the onset and offset times of seizure and result in the achievement of patient-specific parameter tuning for training the detector.

Vukkadala *et al*. (2009) have proposed an automated epileptic EEG Detection System. This is based on Elman neural network which considers the input feature as Approximate Entropy (ApEn). ApEn is said to be a statistical parameter for predicting the current amplitude values based on the earlier values of a physiological signal. They considered that during an epileptic seizure the value of the ApEn drops. The system was evaluated as a whole and its accuracy and efficiency was determined based on recordings from 21 patients. Due to ApEn's robustness and high detection accuracy, this system is said to be an efficient and capable for an automated epileptic EEG detection.

Tout *et al*. (2008) have examined a scheme for predicting epileptic seizure using the concepts of neural networks. The most probable parameters have been applied for inputs of the multilayer neural network that could symbolize the long-term EEG signals. Neural networks have been trained mainly for detecting the ictal and non-ictal patterns and then the prediction capability of the network is being executed. Furthermore, the sensitivity and specificity of the network was predicted. They have also accomplished that only with five parameters taking as inputs of the MLP network; the prediction was achieved to have a high sensitivity and specificity of about 88%.

Subasi *et al*. (2005) have proposed the application of Auto Regressive (AR) Model for detecting epileptic seizure. They used the Artificial Neural Networks (ANNs) and Maximum Likelihood Estimation (MLE) for the interpretation and performance of their method to extract efficient features from human Electroencephalogram (EEG). Classification of every patient into exactly two categories, i.e., epileptic seizure or non-epileptic seizure was established effectively and by testing the accuracy, specificity and sensitivity of ANNs. They have also accomplished the fact that, classification of EEG signals using ANN with AR yield better results.

Bao *et al*. (2008) have presented an analytical system that can employ interictal EEG data for the automatic diagnosis of epilepsy in humans. The system could also detect the activities of seizure in patient for prior examination by doctors and imminent patient monitoring. From the obtained EEG data, three classes of features were extracted and were fed up to in order to build a Probabilistic Neural Network (PNN). Leave-One-Out Cross-Validation (LOO-CV) was used on an epileptic-normal data set and this revealed a remarkable accuracy rate of the system on differentiating normal people's EEG from patients' interictal EEG. Besides, the system can be used in patient monitoring for seizure detection and seizure focus localization. This resulted in an improved accuracy with 96.7 and 76.5% respectively on the data set.

Tezel and Ozbay (2009) have developed diagnostic Neural Network Models with Adaptive Activation Function (NNAAF) for epileptic seizure detection. The proposed NNAAF Models comprise three types namely, NNAAF-1, NNAAF-2 and NNAAF-3. In NNAAF-1 Model, the activation function of the hidden neuron was a sigmoid function including free parameters. Likewise the activation function of hidden neuron in the second model, NNAAF-2 was the sum of sigmoid functions with free parameters and also sinusoidal functions with free parameters. Whereas, Morley Wavelet function with free parameters has the activation function of hidden neuron in the third model, NNAAF-3. Moreover, traditional Multilayer Perception (MLP) Neural Network (NN) Model have been applied in the hidden layer with fixed sigmoid activation function to evaluate the NNAAF Models. Analysis was performed for determining the robustness of these models by means of training and testing using 5 fold cross-validation. They have achieved 100% average sensitivity and specificity and classification rate in all their models.

For the purpose of classifying different types of epileptic seizures, Najumnissa and Devi (2008) have proposed a simple approach using a set of feed forward neural network. This approach along with wavelet feature extraction is used to process time and frequency for detection and classification like absence, Tonic-clonic, Febrile and Complex partial seizures. The proposed model has been tested on EEG thereby revealing a success rate of 94.3%. This potential method makes it prospective as a real-time detector that will augment the clinical service of electroencephalographic recording.

Smart *et al*. (2007) have illustrated a Genetic Programming (GP) application to select and integrate Conventional features (C-features) optimally. This was presented to detect epileptic waveforms within Intracranial Electroencephalogram (IEEG) recordings which occur preceding to the onset of seizures called seizure precursors. Based on the evidence, it is recommended that seizure precursors may confine regions significant for the generation of seizure on the IEEG and epilepsy treatment. They have suggested GP as a most favorable substitute for generating a single feature subsequent to examining the performance of a binary detector which use: genetically programmed features; selecting features based on GP; forward sequentially selected features and visually selected features. Their results have demonstrated that a detector with a genetically programmed feature outshines than the other three approaches, thereby achieving >83.5% sensitivity, positive predictive value of about 78.5 and 93% specificity at the 95% level of confidence.

To detect epileptic seizure segments in the neonatal Electroencephalogram (EEG), Karayiannis *et al*. (2006)

have presented an approach by distinguishing the spectral features of the EEG waveform using a rule-based algorithm combined with a neural network. The rule-based algorithm employed screened-out short segments of pseudo sinusoidal EEG patterns as epileptic based on features in the power spectrum. The conventional feed forward neural networks and quantum neural networks were trained with the output of the rule-based algorithm and their performance was also compared. The results denoted that the trained neural networks, cascaded with the rule-based algorithm, enhanced the performance of the rule-based algorithm working by own. The assessment of their cascaded scheme for the pseudo sinusoidal seizure segment detection exposed its capability of being a building block of the automated seizure detection system under development.

Srinivasan *et al.* (2007) proposed entropy based epileptic EEG detection. There used gradient descent algorithm with adaptive training rate to train the Elman Network (EN) for automated epilepsy detection. They described that network was trained with binary target values represent 0 for normal EEG signal and 1 for epileptic EEG. Husain and Rao (2012) examined the classification of EEG signals. For extracting the defected signal, they used wavelet transform technique. Gradient descent with momentum (traingdm) was incorporated to train the network in this study. The extension of this work focused on determination of elaborated memory architecture and appropriate training algorithms to get more precise results. Harikumar *et al.* (2012) analyzed epilepsy risk level classifications of EEG signals and used backpropagation training functions such as Levenberg Marquardt (LM). Gradient descent with momentum and Gradient Descent with adaptive to train the networks. From the analysis, they concluded that the LM algorithm provided minimized mean square error than other examined backpropagation training functions.

Bardakjian and Chiu (2001) described a mechanism to use hybrid neural networks to be in command of the biological neural networks by determining their variant states. In order to train the neural networks, there used Fletcher-Powell and gradient descent training mechanisms. The training was accelerated considerably by conjugate gradient functions.

PROPOSED WORK

The predominant purpose of this study is to examine the performance of different backpropagation training algorithms for detection of epileptic seizure from EEG signal.

Independent component analysis: The main objective of ICA is to separate the original signal from the mixture of recorded EM signals, assuming that original signals are statistically independent. Fast ICA an iterative fixed point algorithm that uses kurtosis-based contrast function is employed to separate the seizure signal. This algorithm involves a preprocessing stage followed by fixed point iteration.

Neural networks training: Neural networks mimic the human brain in its ability to learn from events happened in the past and apply the same in future to a similar situation. It consists of a number of processing units along with a node function that determines the output of the node. Multilayer perception an important class of neural networks uses supervised learning. One such multilayer network is the backpropagation network. The backpropagation includes four stages in the training algorithm:

- Initialization of weights
- Feed forward
- Backpropagation of errors
- Updating weights and biases

Training the back propagation network is reducing the system error to a minimum. An outline of the proposed approach is illustrated in Fig. 1. Using neural network researchers have classified the EEG signals as normal and interictal. The proposed algorithm in this research is as follows:

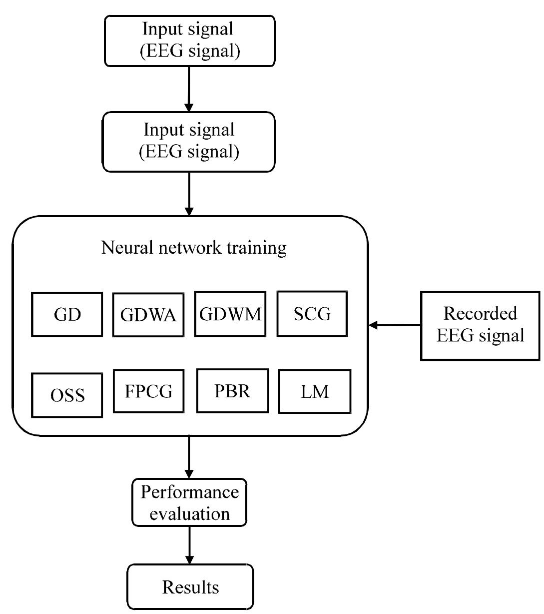

Fig. 1: Block diagram of the proposed epileptic seizure detection with performance comparison

- Load the dataset
- Identify the components related to epileptic seizure detection using fast independent component analysis
- Create a network. Researchers use a feed forward network with the tan-sigmoid transfer function in the hidden layer and output layer. The 15 neurons (subjective) are used in hidden layer. The network comprises two outcome neurons
- Random values assigned to the input weight and bias
- Allocate 80% for training, 10% for validation and remaining 10% for testing
- Train and test the network using Backpropagation algorithm
- Compare the results of training algorithms using accuracy
- Evaluate the neural networks performance by means of mean squared error, confusion matrix and linear regression curve

The process of epileptic seizure detection approach composed of the fast independent component analysis, Backpropagation algorithm neural network training. With the base of the operations mentioned in the above block diagram, researchers proposed an analysis of seizure detection with Backpropagation algorithm trained by various training functions such as Gradient Descent algorithm (GD), Scaled Conjugate Gradient (SCG), One Step Secant (OSS), Powell-Beale Restarts (PBR), Gradient Descent with Adaptive (GDWA) Fletcher-Powell Conjugate Gradient (FPCG) and Levenberg Marquardt (LM) Backpropagation. Consequently, trained neural networks are tested and validated with the stored EEG signals for performing the comparative study over all the training functions mentioned.

Illustrations of back propagation training functions: This study contains the confession of various Backpropagation training functions which researchers have taken for analyzing the performance of network against publicly available EEG dataset in epileptic seizure detection.

Gradient descent algorithm (traingdm): Gradient Descent (GD) with momentum is a predominant training method, implemented by traingdm, concedes a network to retort not only to the confined gradient but also to current trends in the error surface. Acting like a lowpass filter, momentum avows the network to disregard small features in the error plane. Without impetus a network can get wedged in a shallow local minimum. With momentum a system can glide through such a minimum.

Gradient descent with adaptive (traingda): The gradient descent with adaptive backpropagation training rate (traingda) is a network training function that renovates weight and bias values conceding to the gradient descent with adaptive training rate. It also includes the net input/output and transfer functions. The performance of this algorithm is delicate to the given learning training rate. The training functionalities terminate when the maximum number of epochs is attained, exceeds maximum time allotted, minimized performance and the performance gradient drops below the minimum gradient value.

Scaled conjugate gradient (trainscg): Conjugate gradient algorithm craves a line search regarding all iterations. This line exploration is computationally classy. Since, it requires that the network retort to all training inputs is evaluated several times for each search. The Scaled Conjugate Gradient algorithm (SCG) was designed to avoid the time-consuming line search. This algorithm combines the model-trust region approach used in the Levenberg-Marquardt algorithm with the conjugate gradient approach.

The trainscg schedule may require more iteration to congregate than the other conjugate gradient algorithms but the number of estimations in all iteration is significantly reduced since there is no line search is performed.

One step secant (trainoss): Since, the Broyden-Fletche-Goldfarb-Shanno (BFGS) Method acquires more storage and computation in all iteration than the conjugate gradient algorithms, there is necessity for a secant approximation with smaller storage and computation requirements. The One Step Secant (OSS) Method is an effort to bridge the gap between the conjugate gradient algorithms and the Quasi-Newton (secant) algorithms. There is no contingency for storing the complete Hessian matrix; it deduces that at all iterations, the prior Hessian was the identity matrix. This has the supplementary advantage that the new search route can be premeditated without computing a matrix inverse. This algorithm obligates less storage and computation per epoch than the BFGS algorithm and needs slightly more storage and computation per epoch than the conjugate gradient algorithms. It can be cogitated a concession between full Quasi-Newton algorithms and conjugate gradient algorithms.

Powell-beale restarts (traincgb): In Powell-Beale Restarts (PBR), the search direction will be systematically reset to the negative of the gradient for all conjugate gradient algorithms. The reset point will be fixed where the number of iterations is equal to the amount of network parameters (weights and biases) but there are other reset methods that can progress the efficiency of training. One such reset method was projected by Powell. For this practice, researchers will resume if there is very little orthogonally left between the current gradient and the earlier gradient. This is experienced with the following discrimination:

$$\left|g_k^T - 1g_k\right| \geq 0.2\left|g_k\right|^2$$

If this state is satisfied, the search direction is reset to the negative of the gradient.

Fletcher-Powell conjugate gradient (traincgf): The Fletcher-Powell conjugate gradient function (traincgf) updates the weight and bias values including Fletcher-Powell renovate. The input set comprises details about the neural network, delayed input vectors, target vectors, initial input delay conditions, batch size and time steps. The algorithm needs smallest storage requirements than other compared algorithms. Moreover, the training function enormously effects on performance with respect to weight and bias values.

Levenberg Marquard backpropagation (trainlm): Levenberg Marquard backpropagation (LM) is another optimal way of training the neural networks in such a manner producing minimum errors. Trainlm is a network training function that patches weight and bias values in accordance with Levenberg-Marquardt optimization. Trainlm is habitually the fastest backpropagation algorithm in the toolbox and is highly suggested as a first-choice supervised algorithm, even though it requires more memory than other algorithms.

The affirmed research is to analyze the results of the above-mentioned algorithms in terms of Mean Square Error (MSE), epoch value, accuracy and time. In experimental results, researchers figure out the seizure detection rate in testing by the training methods such as gradient descent algorithm (traingdm), scaled conjugate gradient (trainscg), one step secant (trainoss), powell-beale restarts (traincgb), gradient descent with adaptive (traingda), Fletcher-Powell conjugate gradient (traincgf) and levenberg marquardt backpropagation (trainlm).

EXPERIMENTAL RESULTS

Datasets were collected from database Ralph Andrezak (http://epileptologie_bonn.de). The dataset comprises of four different sets, each containing 100 single channel EEG data. Datasets Z and O taken from normal periods were combined. Dataset N and F recorded during seizure free intervals (interictal periods) were combined. Totally 400 EEG signals were used. Dataset was partitioned into three sets-80% for training, 10% for validation and 10% for testing. Three layers are present in the network namely an input layer, hidden layer and output layer with one unit which shows whether the input is normal or not. Input vectors are normalized and connection weights randomized. All the computations are implemented using MATLAB V7 with learning rate of 0.001and maximum number of epochs as 100. First the network was trained using gradient descent algorithm. Mean square error plot for the simulation is shown in Fig. 2.

The above graphical representation shows the accordance between the 100 epochs and the mean square error rate with the gradient descent algorithm without any adaptive and momentum combinations in that. From the above training, researchers predicted that the regression rate of the algorithm is 0.9246 and the MSE is 0.0913. It acquires the maximum iterations that are 100 in number for producing the accuracy rate of 90.75 in 9.6099 sec.

The neural network also is analyzed in gradient descent with adaptive algorithm in spite of the examination of further efficiency. Figure 3 exemplifies the

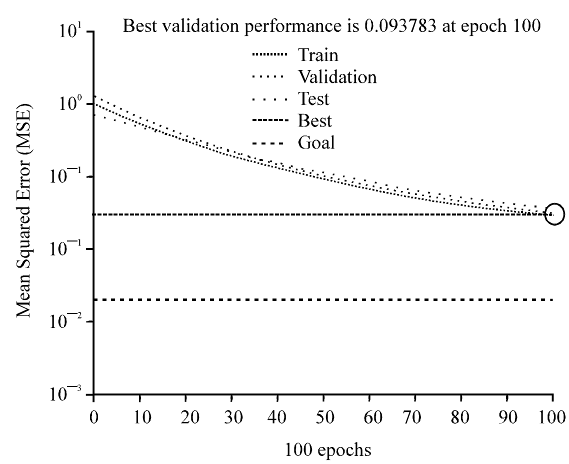

Fig. 2: Gradient descent algorithm

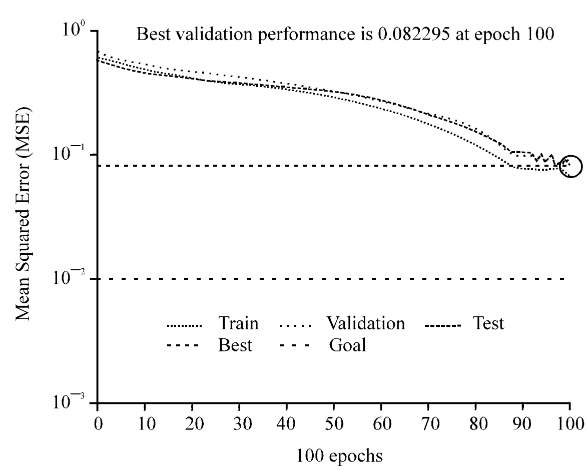

Fig. 3: Gradient descent with adaptive

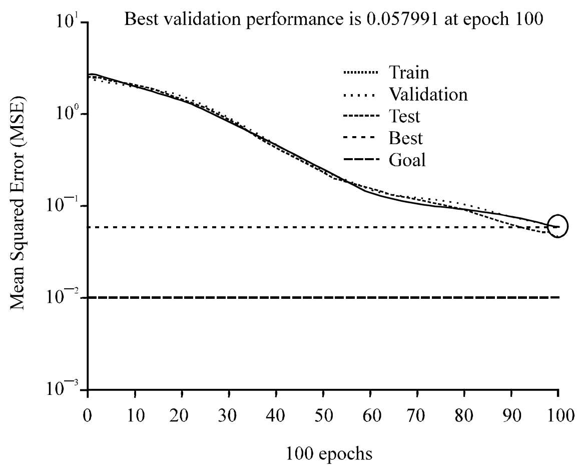

Fig. 4: Gradient descent with momentum

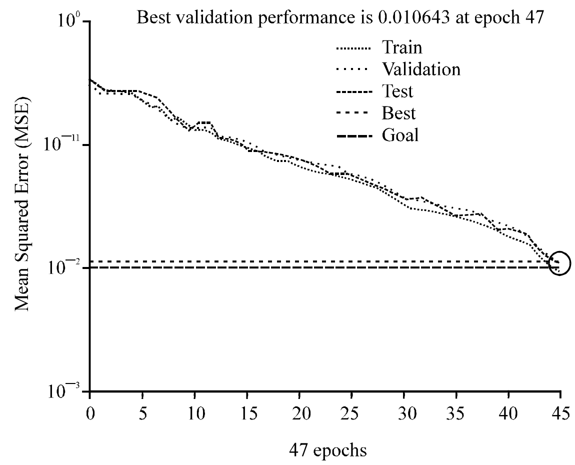

Fig. 5: Scaled conjugate gradient

training performance of the dataset affords the regression rate of 0.93527 and gives the best validation performance at the 100th iteration. The algorithm with adaptive techniques imposes the best validation performance rate of 0.082295. It provides 98.5% accurate results in 9.5387 sec. The study relates with the above methodology gives less efficiency.

The next result analysis is made with the training methodology called gradient descent with momentum. Figure 4 represented the efficiency rate of the gradient descent with momentum algorithm.

The training method provides the regression rate 0.9739. It is glassy that with the complete accommodation of 100 epochs it provides the best validation performance rate 0.057991. The phase gives 100% accurate results with minimum error rate acquiring 100 iterations. The training and testing phase of the above method manifests that reearchers acquire much greater efficiency than this method of network training. The testing phase is operated by departing the EEG signals to the trained network.

The approach for automatic detection of epileptic seizure is then analyzed with Scaled Conjugate Gradient Method where the training of network is represented with trainscg. The process reaches the best validation performance in 47 iterations and at the mean square error of 10^{-1}. The scaled Conjugate Training Method affords 100% accurate results in 8.9952 sec.

Figure 5 enacts the depiction of the results of Scaled Conjugate Gradient Training which provides the regression rate 0.99749. The best validation performance rate of this training is determined as 0.010643. Besides the above methods, the scaled conjugate gradient network training method affords higher performance rate accommodating less epochs and mean square error rate.

Figure 6 represents the performance of training, validation and testing phases and finally the regression rate of SCG. The graphs plotted in the following figure specify the correlation between the target of the prediction algorithm and the output produced by the training function.

Figure 7 demonstrates the confusion matrix for the scaled conjugate gradient algorithm. The confusion matrix of SCG is determined between the target class and the output class. The diagonal values represent the appropriate classification results and the final diagonal value shows the accuracy rate of the classification. The rest of confusion matrix exhibits the misclassification results.

The SCG Method of network training begets 100% accurate results in 8.9952 sec. The examination proceeds with the determination of the efficacy rate of One Step Secant Method of training (Fig. 8). With the referenced dataset, the training methodology gives the best performance rate at its 58th iteration as 0.0092724. The above graph exhibits the correlation between the number of epochs needed for better accurate prediction and the mean square error rate. The results of this training method have the mean square rate of 10^0 which reaches the best performance rate before 100th iteration. The regression rate of this method is evaluated as 0.98877. It affords 100% accurate results with 11.6329 seconds time duration.

Figure 9 demonstrates the performance rate of Powell-Beale Restarts mentioned as traincgb. The regression rate of this training algorithm is 0.9821. The training methodology based on the network parameters such as weights and biases and follows a search direction conceit for efficient results. It attends the best performance rate in the accomplishment of 40 iterations or epochs.

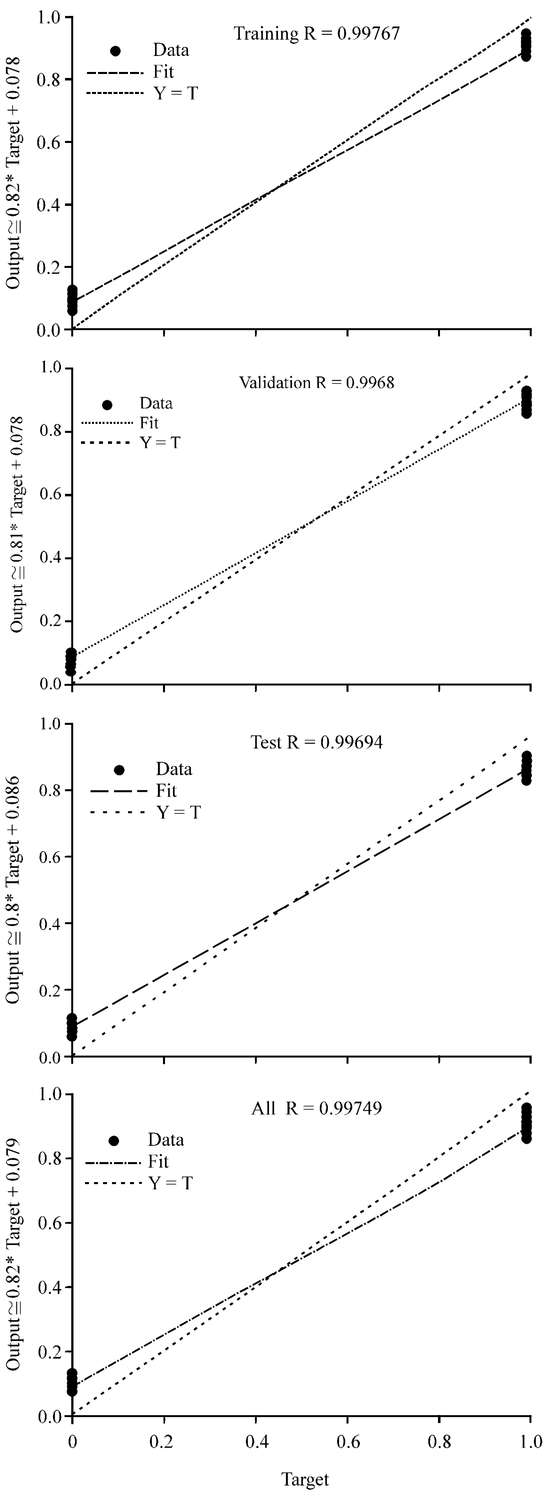

Fig. 6: SCG-regression

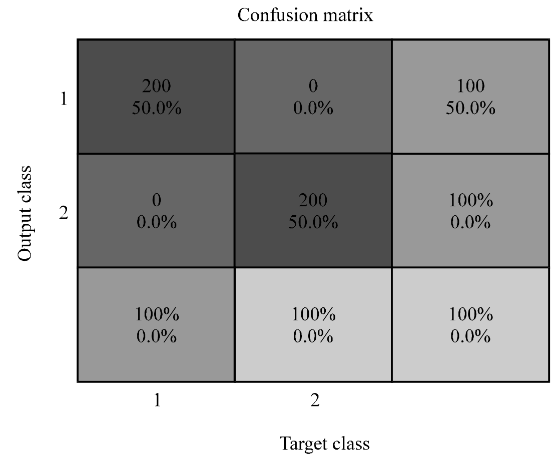

Fig. 7: SCG-confusion matrix

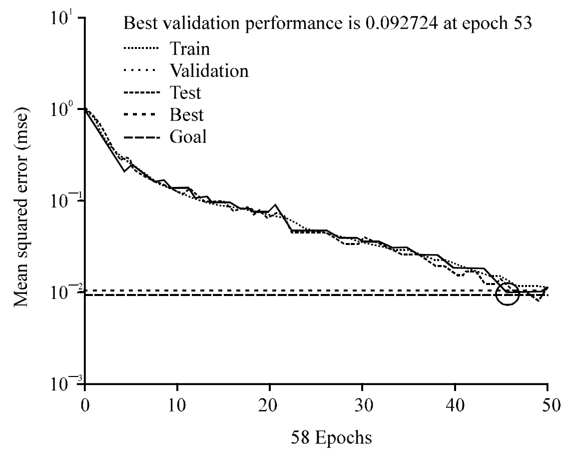

Fig. 8: One step secant

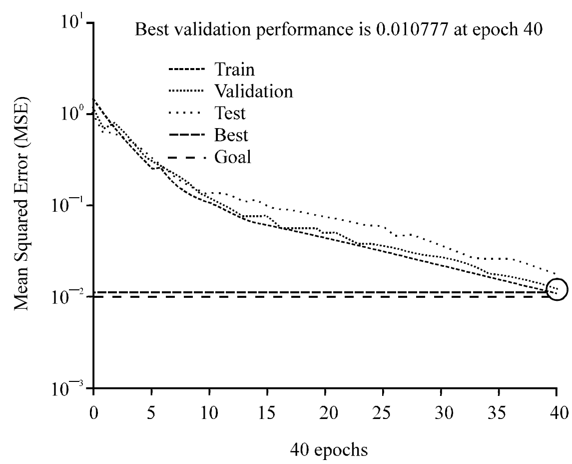

Fig. 9: Powell-Beale restarts

The accuracy rate attained through this training is 100% in 8.3196 sec. The best validation performance is evaluated as 0.010777. The correlation between the mean square rate and the number of epochs is made at 10^{-2} MSE in 40 iterations. The subsequent Fig. 10

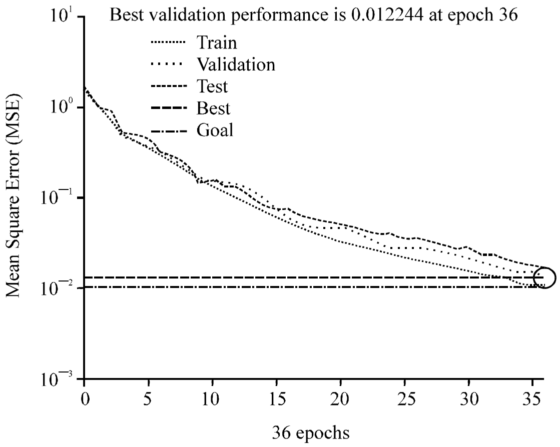

Fig. 10: Fletcher-Powell conjugate gradient

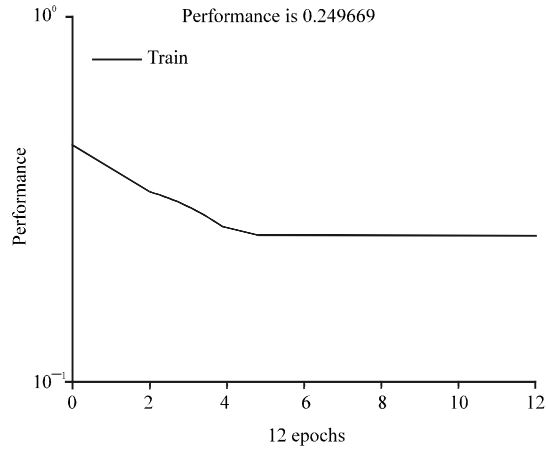

Fig. 11: Levenberg Marquardt backpropagation

demonstrates the result analysis of Fletcher-Powell Conjugate gradient. The best validation performance is attained at 36th iteration and producing 0.012244 performance rate. It produces 100% accurate results in 6.4455 sec.

The training algorithm is termed as traincgf. The best validation rate is acquired with the mean square error value 10^{-2}. The methodology shows its efficiency by utilizing fewer numbers of iteration. The regression rate of this conceit is determined as 0.98227. Fletcher-Powell Conjugate gradient attains the target performance rate with the accomplishment of lower epoch value and less duration but the mean square rate is considerably high in this training methodology.

Figure 11 exhibits the statistical training analysis of levenberg marquardt backpropagation that is demonstrated by trainlm. Though trainlm is habitually the fastest backpropagation algorithm in the toolbox and is highly suggested as a first-choice supervised algorithm, even though it requires more memory than other algorithms it is not suitable for the network training with respect to the constraints. Hence, it produces NaN (not a number) results which could be studied with just 4 iterations. Thus, researchers have analyzed distinct backpropagation training algorithms for better network training for accurate epileptic seizure detection.

The efficiency discrimination of the above explained methodology is made with the terms of mean square ratio, number of epochs, accuracy rate and time needed for producing the results. Table 1 represents the comparison chart for the analysis of the above specified network training classifications.

On comparing the performance of these aforementioned algorithms highest accuracy with lowest mean square error was obtained for scaled conjugate gradient. The above shown comparison chart comprises

Table 1: Table for performance comparison

Training function	MSE	Epoch	Accuracy (%)	Time (sec)
GD	0.0913	100	90.7500	9.6099
GDWA	0.0701	100	98.5000	9.5387
GDWM	0.0492	100	100	9.8426
SCG	0.0092	47	100	8.9952
OSS	0.0121	58	100	11.6329
PBR	0.0105	40	100	8.3196
FPCG	0.0100	36	100	9.8426
LM	0.4450	4	55.5000	29.5872

the results of all the training classifications researchers focused with distinct training functions. The efficacy rate of the classification approach is determined via less MSE, accumulation of lesser number of iterations and higher accuracy rate in accordance with reduced time consumption. Hence, analyzing the results of each mechanism, it is obvious that the scaled conjugate gradient produces high accuracy rate consensus with above mentioned coercions.

CONCLUSION

The imperious antecedent of this study work is to analyze the performance evaluation of distinct training functions in epileptic seizure detection from the recorded EEG brain signals. Independent subcomponents are segregated from the recorded brain signals for the fast independent component analysis, subsequently the signals are trained with some neural network techniques with different training functions such as gradient descent algorithm (traingdm), scaled conjugate gradient (trainscg), one step secant (trainoss), Powell-Beale restarts (traincgb), gradient descent with adaptive, Fletcher-Powell conjugate gradient (traincgf) and levenberg marquard backpropagation (trainlm). From the results of all these training function, the performance evaluation of the trained network in accordance with the recorded EEG brain signals is determined. By the experimental results, the analysis is being consummated with the scaled conjugate gradient is the best training function which provides 100% result accuracy in epileptic seizure detection with limited number of iterations, reduced error rate and reduced time consumption. Researchers plan to extend the proposed research with hardware implementations using the factual results for effective seizure detection from both single and multi-channel datasets.

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