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Research Article

A NEW FRAMEWORK BASED ON EXTREME LEARNING MACHINE FOR EPILEPTIC SEIZURE DETECTION

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ABSTRACT

A sharp cause for the seizure remains within the darker aspect of the detection. To develop correct realizable automatic spike detection improvement methodology has been projected. The reliable application of machine learning strategies becomes progressively vital in difficult engineering domains. especially, the applying of Extreme Learning Machines (ELM) looks promising attributable to their apparent simplicity and therefore the capability of terribly economical process of enormous and high-dimensional knowledge sets. However, the ELM paradigm is predicated on the conception of single hidden-layer neural networks with arbitrarily initialized and glued input weights and is therefore inherently unreliable. The goal is to produce the Extreme Learning Machine approach with the talents to perform dependably in numerous, difficult engineering tasks by exploiting the simplicity, catholicity and procedure potency of the model.

Keywords: Epileptic Seizure Detection, Extreme Learning Machine (ELM), EEG Signals

INTRODUCTION

Epilepsy could be a neurological disorder with prevalence of regarding 1-2% of the world's population. It's characterized by abrupt continual and transient disturbances of perception or behavior ensuing from excessive synchronization of plant tissue neural networks; it's a neurologic condition during which a private experiences chronic abnormal bursts of electrical discharges within the brain. Encephalopathy might be a standard chronic neurological disease characterized by the sharp, generally transient, excessive electrical discharges throughout a cluster of brain neurons. Over fifty million people are diagnosed with brain disease inside the planet. EEG signal analysis is wide used for assessing disorders of brain operate, notably for brain disease diagnosis. the traditional methodology used to confirm seizures is heavily passionate about the visual analysis of the encephalogram recordings by the trained professionals. The Automating the detection of epileptic seizures is effective for serving to neurologists to research the encephalogram recordings, to boot in addition offer solutions for closed-loop therapeutic devices like implantable electrical stimulation systems. An automatic seizure detection strategy inside the diagnosis of encephalopathy was developed inside the first 1970s. In recent years, many algorithms for the detection of seizures are projected and applied, like frequency domain analysis, time-frequency domain analysis, artificial neural network based analysis and machine learning based analysis. For non-stationary encephalogram signals, time-frequency analysis methods, like separate rippling rework (DWT), are tried to be an economical analysis tool and can given quantitative analysis of attack encephalogram in varied frequency bands.

The hallmark of encephalopathy is perennial seizures termed epileptic seizures. Epileptic seizures are divided by their clinical manifestation into partial or focal, generalized, unilateral and unclassified seizures. Focal epileptic seizures involve solely a part of neural structure and turn out symptoms in corresponding elements of the body or in some connected mental functions. Seizures are transient aberrations within the brain's electrical activity, individuals with encephalopathy, and a central nervous system disorder, suffer from perennial seizures that occur at unpredictable times and typically unexpectedly. Seizures may result in an exceedingly lapse of attention or a whole-body convulsion. Frequent seizures increase an individual's risk of sustaining physical injuries and should even lead to death. a tool capable of quickly detection and reacting to a seizure by delivering medical aid or notifying a caregiver might ease the burden of seizures. Generalized epileptic seizures involve the whole brain and turn out bilateral motor symptoms typically with loss of consciousness. Each kind of epileptic seizures will occur in any respect ages. Generalized epileptic seizures may be divided into absence (petit mal) and tonic-clonic (grand mal) seizures. Observance of brain activity through the electroencephalogram (EEG) has become a crucial tool within the designation of encephalopathy. The EEG recordings of patients plagued by encephalopathy show 2 classes of abnormal activity: inter-ictal, abnormal signals recorded between epileptic seizures; and ictic, the activity recorded throughout an epileptic seizure (Fig. 1). The EEG signature of an inter-ictal activity is occasional transient waveforms, as isolated spikes, spike trains, sharp waves or spike-wave complexes. EEG signature of an epileptic seizure (ictal period) consists of an eternal discharge of polymorphic waveforms of variable amplitude and frequency, spike and sharp wave complexes, rhythmical hypersynchrony, or electrocerebral inactivity ascertained over a period longer than the common period of those abnormalities throughout inter-ictal periods.

EEG-based analysis works on seizure detection adopt unremarkably one altogether the these a pair of major approaches: Examination of the morphology and topography of waveforms in inter-ictal stage to look out events (markers) or changes in cell activity which can be precursors to seizures, and analysis of the nonlinear spatiotemporal patterns of encephalogram signals to inform apart seizure-free state from seizure state. The second approach was adopted throughout this study to assess encephalogram signals for convulsion detection. Supported the recent studies of the community of neurophysiologic researchers, encephalogram signals are variable data point stem from very nonlinear and two-dimensional systems. Hence, our projected methodology includes a nonlinear data point analysis. However, since the encephalogram information embrace the transient signals embedded in noise and non-stationary signals, nonlinear time-series analysis got to be administrated with caution and it's higher to choose a method that does not want assumptions regarding stationarity, length of signal, and noise. Extreme learning machine (ELM), that has constant requirements, has been utilized in and to follow transitions from interictal to attack quantity. in addition, results of recent investigations indicate that in some cases, encephalogram subbands delta (0–4 Hz), alphabetic character (4–8 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (30–60 Hz) might yield extra correct information regarding constituent cell activities underlying the encephalogram, and consequently, sure changes inside the encephalograms that are not evident inside the first full-spectrum EEG might even be amplified once each subband is analyzed separately.

The most common way to infer the onset of a seizure before it becomes clinically manifest is through analysis of the scalp graphical record (EEG), a non-invasive, multi-channel recording of the brain's electrical activity. The characteristics of EEG vary considerably across patients. In fact, EEG related to seizure onset in one patient could closely match a benign pattern inside the EEG of another patient.

A common approach in seizure recognition/detection and additionally in prediction is to extract information; in alternative words, options that may characterize seizure morphologies, from EEG recordings. The procedure for feature extraction from multi-channel EEG information is usually as follows: initial, an EEG signal from a channel is split into I time epochs (overlapping or non-overlapping) and so J options are extracted from every epoch. Consequently, a proof from one channel may be described as a matrix of size I × J. a good deal of effort from completely different disciplines has been invested with in exploring the options so as to outline the signature of a seizure. These options embody applied mathematics quality measures (e.g., pattern dimension, approximate entropy, lyapunov exponents, etc.) in addition as alternative options from time (e.g., higher-order statistics of the signal in time domain, Hjorth parameters, etc.) and frequency domains (e.g., spectral lopsidedness, spectral entropy, etc.). an inventory of options employed in characterization of epileptic seizure dynamics may be found in recent studies.

Existing Method

The SVM designed on statistical learning theory was developed by Hernan Cortez and Vapnik (1995) for binary classification, and is currently wide employed in pattern classification. The thought of SVM formula is to project nonlinear dissociable samples onto another higher-dimensional house by kernel functions, so find the Optimum Separating Hyperplane (OSH) within the projection space by resolution a quadratic optimization problem. Typical kernel functions of SVM are linear kernel, polynomial kernel, Radial Basis Functions (RBF), and sigmoidal neural network kernel. Satisfactory results were achieved by exploitation RBF kernel perform, that is outlined by the worth of the SVM output, was outlined as one or one, that one represents the normal/non-seizure electroencephalogram and one represents the seizure electroencephalogram. However, the worth of the SVM output is not invariably one or one, typically dynamical within the interval [1 1]. For this reason, postprocessing for the SVM outputs is critical. The postprocessing theme consists of smoothing, multi-channel decision fusion, and collar technique.

Fig 1. shows the post process theme for patient 14 throughout the seizure at the 17th hour. (a) The raw detection output of the SVM classifier with channels one. (b) The smoothened output when the moving average filtering. (c) The binary selections with channel 1 when thresholding. (d) The binary selections with channel 2 when thresholding. (e) The binary selections of channel 3 when thresholding. (f) The binary selections once 3 channels are fused. (g) The ultimate binary selections when the collar operation, that will increase the length of all positive selections. (h) The bottom truth, wherever 1 indicates seizure.

Extreme Learning Machine

A Brief Description of Extreme Learning Machine

Single Layer Feed forward Network (SLFN) could fix then connections on one level (i.e., weights between input neurons and hidden neurons) and only change the connections on the opposite level (i.e., weights between hidden neurons and output place neurons) and there's no gain achieved by an algorithmic program ready to change the weights on each levels at the same time. Huang et al, planned a brand new learning algorithmic program mentioned as Extreme Learning Machine (ELM). ELM indiscriminately chooses and fixes the weights between input neurons and hidden neurons supported some continuous likelihood density operate, so analytically determines the weights between hidden neurons and output neurons of the SLFN.

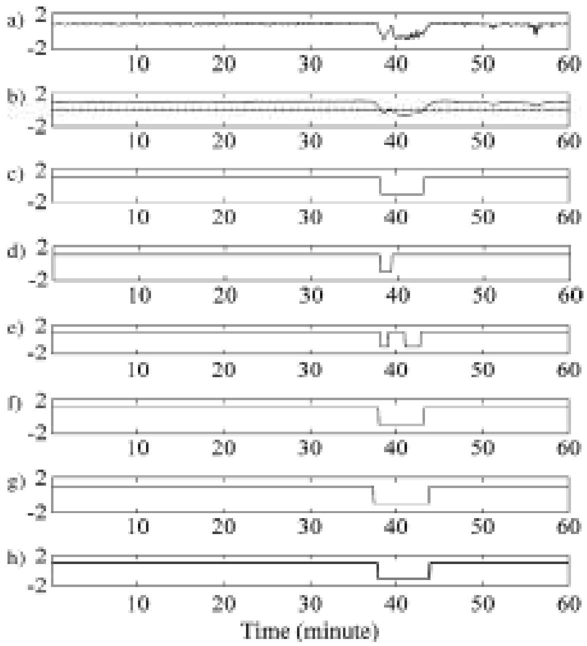


Figure 1: Post processing Scheme

Machine learning and artificial intelligence have apparently never been as essential and vital to real-life applications as they're in today's autonomous, huge information era. The success of machine learning and computer science depends on the being of 3 necessary conditions: powerful computing environments, made and/or massive information, and economical learning techniques (algorithms). the Extreme Learning Machine (ELM) as an rising learning technique provides economical unified solutions to generalized feed-forward net-works as well as however not restricted to (both single- and multi-hidden-layer) neural networks, radial basis operate (RBF) networks, and kernel learning.

ELM was originally planned for the single-hidden-layer feed forward neural networks and was then extended to the generalized SLFNs wherever the hidden layer needn't be nerve cell alike. In ELM, the hidden layer needn't be tuned. The output operate of ELM for generalized SLFNs (take one output node case as an example) is

$$f_L(x)=\sum_{i=1}^{L} \beta_i h_i(x) = h(x)\beta \qquad (1)$$

Where $\beta=[\beta_1,...,\beta_L]^T$ is the vector of the output weights between the hidden layer of L nodes and the output node and $h(x)=[h_1(x),...,h_L(x)]$ is the output (row) vector of the hidden layer with respect to the input x.h(x) actually maps the data from the d-dimensional input space to the L-dimensional hidden-layer feature space (ELM feature space) H, and thus, h(x)is indeed a feature mapping. For the binary classification applications, the decision function of ELM is

$$f_L(x) = \text{sign}(h(x)\beta) \qquad (2)$$

Different from ancient learning algorithms, ELM tends to achieve not solely the tiniest coaching error however conjointly the littlest norm of output weights. According to Bartlett's theory, for feed forward neural networks reaching smaller coaching error, the smaller the norms of weights are the higher generalization performance the networks tend to own. We have a tendency to conjecture that this might be faithful the generalized SLFNs wherever the hidden layer might not be nerve cell alike. ELM is to reduce the training error moreover because the norm of the output weights.

$$Minimize \; : \|H\beta - T\|^2 \; and \; \|\beta\| \qquad (3)$$

Where H is the hidden-layer output matrix

$$H = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_N) \end{bmatrix} = \begin{bmatrix} h_1(x_1) & \cdots & h_L(x_1) \\ \vdots & \vdots & \vdots \\ h_1(x_N) & \vdots & h_L(x_N) \end{bmatrix} \qquad (4)$$

Seen from (2), to minimize the norm of the output weights β is actually to maximize the distance of the separating margins of the two different classes in the ELM feature space: 2/β. The minimal norm least square method instead of the standard optimization method was used in the original implementation of ELM.

$$\beta = H^{\ell} T \qquad (5)$$

Where H^{ℓ} is the Moore–Penrose generalized inverse of matrix H. Different methods can be used to calculate the Moore–Penrose generalized inverse of a matrix: orthogonal projection method, orthogonalization method, iterative method, and singular value decomposition (SVD).

Approximation problem of SLFNs

For N samples $\{(\mathbf{x}_k, \mathbf{t}_k)\}_{k=1}^{N}$, where $\mathbf{x}_k = [x_{k1}, x_{k2,....,} x_{kn}]^T$ and $\mathbf{t}_k = [t_{k1}, t_{k2}, ...t_{km}]^T$, a standard SLFN with ˜N hidden neurons and activation function g(x) is mathematically modeled as,

$$\sum_{i=1}^{N} \beta_i g(w_i . x_k + b_i) = o_k, \quad k = 1,....., N. \qquad (6)$$

where $\mathbf{w}_i = [w_{i1}, w_{i2}, . . ., w_{in}]^T$ is the weight vector connecting the i^{th} hidden neuron and the input neurons, $\beta_i = [\beta_{i1}, \beta_{i2}, . . . , \beta_{im}]^T$ is the weight vector connecting the i^{th} hidden neuron and the output neurons, $\mathbf{o}_k = [o_{k1}, o_{k2}, . . . , o_{km}]^T$ is the output vector of the SLFN, and bi is the threshold of the i^{th} hidden neuron. $\mathbf{w}_i \cdot \mathbf{x}_k$ denotes the inner product of $\mathbf{w}_i$ and $\mathbf{x}_k$ and these N equations can be written compactly as:

$$H\beta = O \qquad (7)$$

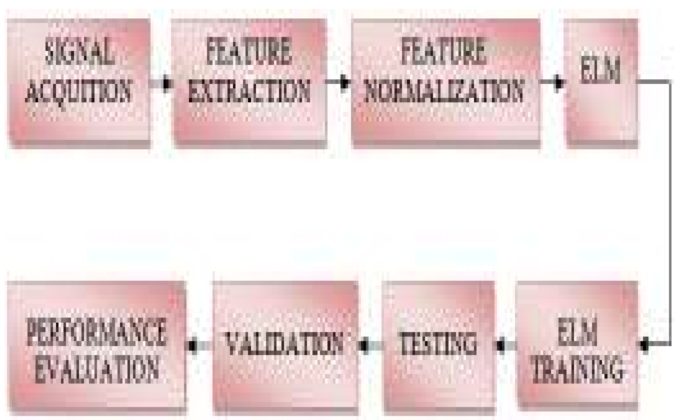
Where

$$H = \begin{bmatrix} g(w_1.x_1 + b_1) & \cdots & g(w_{\tilde{N}} \cdot x_1 + b_{\tilde{N}} \\ \vdots & \ldots & \vdots \\ g(w_1.x_N + b_1) & \cdots & g(w_{\tilde{N}}.x_N + b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}} \qquad (8)$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N} \times m} \quad (4) \qquad O = \begin{bmatrix} o_1^T \\ \vdots \\ o_N^T \end{bmatrix}_{N \times m} \quad (9)$$

Here H is called the hidden layer output matrix.

ELM BLOCK DIAGRAM



Signal Acquition:

Review Electrodes are used to acquire the electroencephalogram signals from the scalp of the human brain. The electroencephalogram recording electrodes and their correct function are crucial for exploit top quality knowledge.

Different types of electrodes are typically employed in the EEG recording systems, such as:

- Needle electrodes
- Headbands and conductor caps
- Disposable electrodes: gel less, and pre-gelled kind
- Reusable disc electrodes: gold, silver, stainless-steel, or tin

The electroencephalogram signal represents voltage distinction between 2 electrodes; one or additional electrodes need to be set as reference so the output voltage will be measured with regard to that indicator. There are numerous systems of taking reference, most typical being the connected ears, that is a mean of the voltage of the electrodes connected to either earlobes or mastoids. The raw graphical record signals obtained from the electrodes have amplitudes of the order of small volts and contain frequency elements of up to 300 cycles per second. The signal is amplified more or less 10,000 times.

High pass filters with a cut-off frequency of typically but 0.5 cycles per second are used to take away the disturbing terribly low frequency elements like those of respiratory. On the opposite hand, high-frequency noise is satisfied by mistreatment low pass filters with a cut-off frequency of roughly 50–70 cycles per second. Notch filters with a null frequency of 50cycle per second are typically necessary to make sure good rejection of the robust 50 cycle per second power provide. The signals square measure reborn to digital kind by mistreatment ADC to store the signal in an exceedingly processed system. Combination of low noise, high gain accuracy, and low gain temperature constant and high dimensionality create the AD620 (shown in Fig 2) ideal to be used in high resolution knowledge acquisition systems.

Figure 2: Sample EEG Acquisition Process*

Feature extraction

In the graph signals, feature extraction is done before the classification method victimization modeling techniques, like Autoregressive (AR) model[19-20]. AR model has been used for graph analysis. The model order that we tend to used here is six, and for mental task classification victimization identical graph information. Thus we tend to deploy a sixth order AR model to suit into half-second graph segments. The coefficients of the model for every section are calculable by the town methodology, and so created into a 36-D feature vector.

ELM learning algorithmic rule

In the case of learning an arbitrary perform with zero training error; Baum had given many constructions of SLFNs with adequate hidden neurons. However, in follow, the amount of hidden neurons needed to attain a correct generalization performance on novel patterns is far less. And therefore the ensuing coaching error might not approach to zero however is reduced by finding the subsequent problem:

$$\min_{Wt,bt,\beta} \left\| H(w_1 \ldots w_{\tilde{N}}, b_1 \ldots\ldots b_{\tilde{N}})\beta - T \right\|^2 \qquad (10)$$

where,

$$T = \begin{bmatrix} t_1^T \\ . \\ . \\ . \\ t_N^T \end{bmatrix}_{N \times m} \qquad (11)$$

ELM randomly assigns and fixes the input weights **w***i* and biases *bi* based on some continuous probability distribution function in the case of learning a structured function, only leaving output weights *βi* to be adjusted according to:
*Image courtesy of Emotiv Systems at
[http://abstractotech.blogspot.in/2012/07/neuro-tech-at-peak-epoc-neuroheadset-by.html]

$$\min_{\beta} \|H\beta - T\|^2 \quad (12)$$

The above problem is well established and known as a linear system optimization problem. Its unique least-squares solution with minimum norm is given by:

$$\hat{\beta} = H^{\ell} T \quad (13)$$

where H^{ℓ} is the Moore-Penrose generalized inverse of the matrix **H**. As analyzed by Bartlett16 and Huang, the generalization performance of a SLFN tends to be better with smaller magnitude of output weights. From this sense, the solution produced by ELM in Eq. (13) not only achieves the minimum square training error but also the best generalization performance on novel patterns. We now summarize ELM as the follows:

ELM Algorithm: Given a training set $N = \{(x_k, t_k) \mid x_k \in R^n, t_k \in R^m,\ k = 1, \ldots, N\}$, an activation function g(x), and the number of hidden neurons $\overline{N}$,

(i) Randomly assign input weights $\mathbf{w}_i$ and biases b_i according to some continuous probability density function.
(ii) Calculate the hidden layer output matrix **H**.
(iii) Calculate the output weights $\beta_i :\ = \mathbf{H}^{\ell}\mathbf{T}$.

In our experiments with ELM in this paper, the activation function is a sigmoidal function: $g(x) = 1/(1 + e^{-x})$ and the probability density function is a uniform distribution function in the range from −1 to 1.

Feature normalization:
Normalize a feature vector to possess unit norm applicable for distributed options. The 2 styles of normalization is combined. Neutralize the result of various scales across options (geometric classifiers are sensitive to that)[19-20].

- Standardization
- Scaling to [0, 1]

Validation:
Two totally different signals in encephalogram analysis area unit described within the knowledge sets that were wont to take a look at varied problems associated with activity validation: the graph itself, and induced potentials. Human expertise of encephalogram analysis has schooled North American nation that it's troublesome to separate validation aspects from interpretation/diagnosis. Still, we've used human consultants as a reference for the performance of our automatic ways. Therefore, we've tried to style objective analysis procedures for the human assessment. Special focus is on the aspects associated with accuracy and signal context. Evoked potentials (EPs) are settled signals which will be obtained from advanced process of the encephalogram, usually recorded throughout a perennial task. Associate voltage represents the electrophysiological behavior of a particular neural pathway, as measured on the scalp. We took the validation of EPs one step more than validation of EEGs: we have a tendency to performed physical object detection, and particularly centered on objective assessment of signal quality.

Performance analysis
Performance analysis and comparison are administered in terms of training time and testing accuracy. The pre-estimated optimum classifier parameters were applied for every classifier[15-18]. So each was trained victimization the training knowledge set obtained from every session. The most effective testing accuracies for every mental task for varied sessions are highlighted. Average testing accuracy over all sessions is given within the last four rows at the side of variance. It is seen from the table one that ELM produces similar accuracy compared with SVM classifiers. Within the present theme, we have a tendency to get the accuracy of 98.67%. This can be due to the periodic nature of the classifier's outputs. The Fig three shows the Input encephalogram Signal and Fig 4 shows the statistical feature values for the corresponding encephalogram Signal.

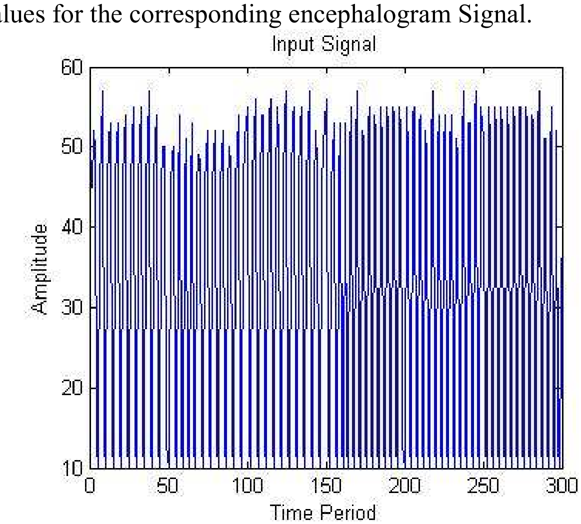


Figure 3. Input EEG Signal

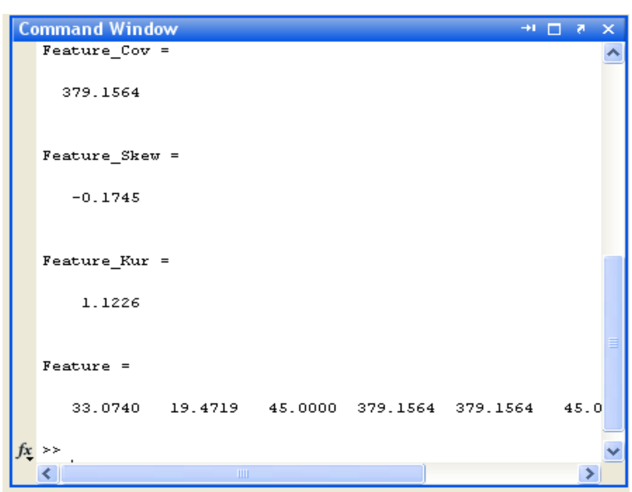


Figure 4. EEG Signal Feature values

COMPARISON OF THE RESULTS OBTAINED BY THE PROPOSED METHOD AND OTHER METHODS

Table1. Comparison between the existing and proposed methods accuracies

Group	Method	Subsets used	Accuracy
Guler et al.[10]	Lyapunov exponents, recurrent neural network(RNN)	Z,F,S	96.79%
Sadati et al.[11]	Discrete wavelet transform(DWT),adaptive neural fuzzy network(ANFN)	Z,F,S	85.9%
Ghosh dastiar et al.[12],[13]	Mixed band wavelet chaos , levenberg marquardt back propagation neural network	Three subsets(unknown labels)	96.7%
Tzallas et al.[14]	Time frequency(TF) analysis, adaptive neural network(ANN)	Z,F,S	99.28%
Tzallas et al.[14]	Time frequency(TF) analysis, adaptive neural network(ANN)	(Z,O),(N,F),S	97.72%
Carlos Guerrero-Mosquera [12]	Support vector machine(SVM)	Three subsets	76.67%
Our work	ELM on EEG signal	Three subsets	98.67%

CONCLUSION

In this paper, we have evaluated the performance of ELM on the classification of mental tasks based on EEG signals. The study indicates that ELM needs about 1 to 2 orders of magnitude less training time compared with SVMs. The classification accuracy of ELM is similar to SVM. Furthermore, the time taken to search the optimal classifier parameters for ELM is significantly lower than the other two classifiers. Also, significant improvement in the testing accuracy can be achieved by smoothing their raw outputs.

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Biography:

Parthiban K G received his ME in Process Control & Instrumentation from Annamalai University (2005) and persuing his PhD degree in Computer Science Engineering from Anna University, Chennai (Jan 2009). He is currently serving as Associate Professor in MPNMJ Engineering College, Chennimalai, Erode. He has 11years of teaching experience. He has published more than 25 research papers in various National and International conference proceedings. Also he published One books on “Electric Circuits and Electron Devices” from Sri Krishna publishers, Chennai. Also he published two national journals in Bio Medical field. His area of interest includes Soft Computing techniques and Bio medical signal processing.

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