Implementation of Epileptic EEG using Recurrent Neural Network

M. Gayatri*, Arun Kumar*, Manish Janghu*, Mandeep Kaur**and Dr. T.V. Prasad***
* Student of Computer Science & Engineering, Lingaya's University, Faridabad, Haryana, India
**Asst. Professor of Computer Science & Engineering, Lingaya's University, Faridabad, Haryana, India
***Professor & Head of Computer Science & Engineering, Lingaya's University, Faridabad, Haryana, India

Summary
The ambulant EEG (electroencephalogram) signal plays an important role in the diagnosis of epilepsy but data recordings generate very lengthy data in the detection of epilepsy which is very time consuming. The traditional method of analysis being tedious, many automated diagnostic systems for epilepsy has emerged in recent years. This paper proposes reason for epilepsy, different type of seizures, stage of epilepsy in patient and how it can be implemented using Artificial Neural Network naming Elman Neural Networks. We know that the value of the ApEn drops sharply during an epileptic seizure so we used it as an input feature. ApEn is a statistical parameter that measures the predictability of the current amplitude values of a physiological signal based on its previous amplitude values. ApEn is used for the first time in the proposed system for the implementation of epilepsy using neural networks.

Key words:
Approximate entropy, Artificial Neural Network, Epilepsy Electroencephalogram (EEG), Elman Neural Network, Seizure.

1. Introduction

Epilepsy is a general term used for a group of disorders that cause disturbances in electrical signaling in the brain. Like an office building or a computer, the brain is a highly complex electrical system, powered by roughly 80 pulses of energy per second. These pulses move back and forth between nerve cells to produce thoughts, feelings, and memories. So, an epileptic seizure occurs when these energy pulses come much more rapidly-as many as 500 per second for a short time-due to an electrical abnormality in the brain. This brief electrical surge can happen in just a small area of the brain, or it can affect the whole brain. Estimated 1% of world population suffers from epilepsy, while 85% of them live in the developing countries. Mainly seizures are of two types i.e. partial (which is restricted to given localized area) and generalized (entire brain is involved).Now partial can be of two types simple partial (20% in adults) and complex partial (40% in adults). Also generalized can be generalized absence (10%, but mostly in children) and tonic clonic (20%). Occurrence of recurrent seizures in the EEG signal is characteristics of epilepsy. Seizures cannot be predicted in a short period, a continuous recording of the EEG is required to detect epilepsy. The entire length of the EEG recordings is analyzed by expert to detect the traces of epilepsy which take up to one week [1]. So many automated epileptic EEG detection systems have been developed in past and artificial neural networks have been used recently. In our system we are having database of 500 patient which are actually text files prepared by doctors for testing of epilepsy. These text files containing integer values which were converted by doctor with his system .Each data set contains 100 single-channel EEG segments, with segment duration of 23 s.

These segments are selected and cut out from the continuous multichannel EEG recordings after visual inspection for artifacts, e.g., due to muscle activity or eye movements. Those which are related to epileptic data sets are obtained from five different epileptic patients recorded during the occurrence of the epileptic seizures from intracranial electrodes. All segments are selected those which exhibiting ictal activity.

Analysis of epileptic EEG is done from the depth electrodes because onset of seizures could be applied to scalp records. And the second data set corresponds to the normal case whose EEG recordings are taken from five healthy subjects using standardized electrode placement technique. The subjects are relaxed in an awaken state with eyes open. The EEG signals are recorded with 128-channel amplifier system, using an average common reference. The Entropy Analysis of EEG Signals is shown in Fig 1.

After a 12-bit analog-to-digital conversion, the data are written continuously onto the disk of a data acquisition computer system at a sampling rate of 173.61 Hz with band pass filter settings at 0.53–40 Hz (12 dB/octave) [1] [18].

This paper discusses an implementation of automated epileptic EEG detection system using neural network which having five modules naming preprocessing module, signal storing, classification module, segmentation module and output module.

Manuscript received March 5, 2010
Manuscript revised March 20, 2010

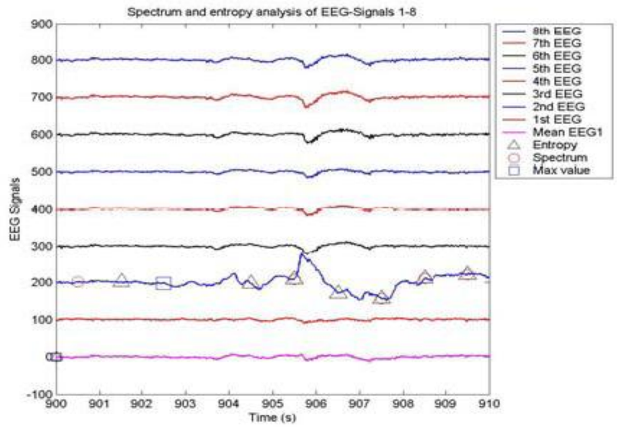

Fig 1. Entropy Analysis of EEG Signals [20]

For training we use Elman Network that uses ApEn as an input feature which measures the predictability of future amplitude values of the EEG based on the one or two previous amplitude values. ApEn drops abruptly due to the synchronous discharge of large groups of neurons during an epileptic activity. So, it is a good feature for using it in the implementation of automated detection of epilepsy [19].

2. Related work

In 1982, Gotman presented a computerized system for detecting a variety of seizures. He proposed that On the basis of decomposition, the EEG tracing can be replaced by using selective recording of the ictal and intercital epileptic activity into the elemenatary waves and also paroxysmal burst of rhythmic activity can be detected having frequency between 3 and 20 c/sec. Simple procedures are used to measure the amplitude of waves relative to the background, their duration and rhythmicity [1] [3].

In 1991, Murro *et al* proposed a automated computerized technique which uses discriminant analysis and three measured EEG features i.e. relative amplitude, dominant frequency and rhythmicity which detect the EEG seizures automatically. He recorded EEG signal from intracranial electrodes and applied to successive non overlapping 2-channel EEG epochs for the seizure detection. And his detection sensitivity ranges from 90% to 100% which was associated with a false positive detection rate of 1.5-2.5/h but performance remained stable [1] [4].

In 1997 Qu and Gotman designed patient-specific classifiers which is a seizure warning system and allow patients and observer to take appropriate precautions. They used a classifier for training which is used after a seizure and some non-seizure data are recorded in a patient. If EEG patterns pass those classifiers in subsequent monitoring sessions during seizure onset then an alarm is triggered. They used time and frequency domains and a modified nearest-neighbor classifier for feature extraction. Their system was effective and reliable and having minimum computational load [1] [5].

In 2004 Gigola *et al*, used a method based on the evolution of the accumulated energy using wavelet analysis for the prediction of the epileptic seizure onset from the intracranial epileptic EEG recordings.[1] [6].

Weng and Khorasani proposed a algorithm which is based on adaptively adjusting the multi-layer back propagation network which belongs to neuron generating strategies rather than neuron pruning .In his algorithm, initially he selected a “small” multi-layer perceptron network and then by using a stabilized error as an index for determining whether the network needs to generate a new neuron or not. After learning that error is stabilized and if the error is larger than desired output then new neuron will be generated and placed at locations that contribute most to the network error behavior through the fluctuation in their input weight vectors. This algorithm reduces the training epoch by 60-70 % as compared to a back-propagation algorithm. The main motive of this algorithm is to provide advantages and capabilities to the application of EEG automatic epileptic seizure detection. This system reduces the false seizure detections to zero while resulting in a 5.1% error in identifying the true seizures [1] [7] [8].

Pradhan *et al* said traditional system for spike detection shows false positive result during long-term epilepsy monitoring because of numerous artefacts and non-epileptic transients. So, for reducing false detection, they provide spike detection sensitive to the state of the EEG. They uses a raw EEG signal as an input to a learning vector quantization (LVQ) network which is a prototype based supervised classification algorithm. It is a special case of Artificial Neural Network which applies winner-take-all learning Hebbian learning based approach. It is a precursor to Self-organizing maps and related to neural gas and to the k-Nearest Neighbor algorithm. Their system classified the states i.e. active wakefulness, quiet wakefulness, desynchronized EEG, phasic EEG and slows EEG [1] [9].

In 2004, Nigam and Graupe proposed a new neural network model called Large Memory Storage And Retrieval (LAMSTAR) network which analyze input words for the search and retrieves information of patient. LAMSTAR includes selection of a module by self organizing map (SOM) which contains the same dimension of classification as a selected input word and where neurons are interconnected horizontally (between modules) and vertically (at input and inside a module) by arrays of link weights. Determination of what nodes or processing units within the SOM need to be activated and subsequently comparison to the selected input word is done by system. By adjusting the weights, feedback is utilized so that the system can learn the best method for acceptable decision or output. This system uses two input feature namely, relative spike amplitude and spike rhythmicity which are time –domain attributes for EEG [1] [10].

Kiymik *et al* used a feed forward ANN system for training and backpropagation for testing, by using a large data set of examplers. On the basis of similar patterns they categorized the seizures. Features are calculated from each segment which is broken from EEG channel having stationary characteristics. After this all segments are clustered of similar morphology. They used periodogram and autoregressive (AR) power spectrum methods as the input feature for network [1] [11].

3. Poposed work

The proposed system consists of following various modules which are also shown using a flowchart in Fig 2.

3.1 Artificial Neural Network

In this a human neuron uses as a model for creating an electronic neuron. The exact algorithm that we used in our neurons for the "thinking" done by a single neuron:

```
Public Sub Think ()
Dim Sum as Single, D as Dendrite
For Each D in Dendrites
  D.Value = D.FromNeuron.AxonValue
  Sum += D.Value * D.Weight
Next
AxonValue = -2 / (1 + Math.Exp (2 * Sum)) + 1
End Sub
```

We left some code here which is to deal with odd cases which are not essential and choose “sigmoid” output function.

3.2 The Network

A layer in this context is just a set of neurons that all share the same inputs. That is, every neuron in one layer has dendrites that extend to all the axons of neurons in a prior layer. The first layer is input layer in which neurons don’t have any dendrites. The neurons themselves are just placeholders so the next layer can tap into these input values in the same way each subsequent layer does.

The last layer is referred to as the "output" layer. Layers between the input and output layers are generally referred to as "hidden" layers. The first layer is just for dumping input values into the network. The second is the output layer, and its neurons are tasked with identifying characters from an input image. Two layers are good for feature extraction but we add another layer for abstraction. So, it is apparent that we could extend this concept further and add any number of layers to add new levels of abstraction and behavior.

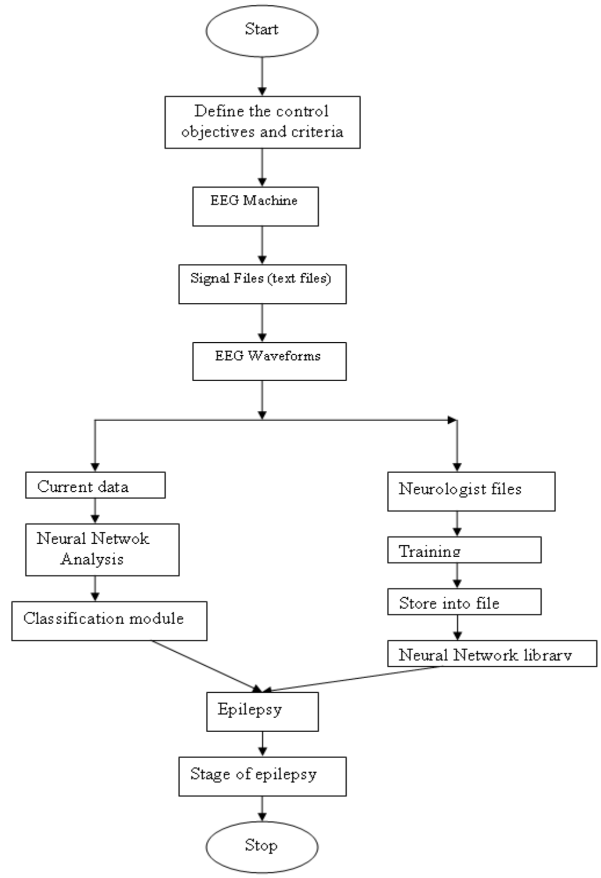

Fig 2. Proposed System

3.3 Elman Network

It is a special type of recurrent neural network where connections between units form a directed cycle as shown in Fig 3. This creates an internal state of the network which allows it to exhibit dynamic temporal behavior. It is a three-layer network with the addition of a set of "context units" in the input layer. There are connections from the middle (hidden) layer to these context units fixed with a weight of one. At each time step, the input is propagated in a standard feed-forward fashion, and then a learning rule is applied. The fixed back connections result in the context units always maintaining a copy of the previous values of the hidden units (since they propagate over the connections before the learning rule is applied).

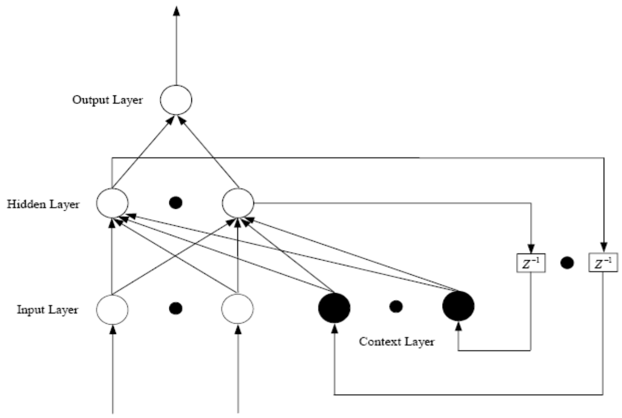

Fig 3. Structure of Elman neural network

Thus the network can maintain a sort of state, allowing it to perform such tasks as sequence-prediction that is beyond the power of a standard multilayer perceptron. Both of the Jordan and Elman networks have fixed feedback parameters, and there is no recurrence in the input-output path. These networks can be trained approximately with straight back propagation. Elman's context layer receives input from the hidden layer, while Jordan's context layer receives input from the output [15].

3.4 Training

In NN we give examples of patterns for learning, so that it can recognize them thereafter, without any designer explicitly calculating what the weights should be. The concept of learning in a single neuron is introduced instead of collective function of a network of neurons. The training cycle is repeated several times, since with each step, the dendrite values are morphed around a small part of the way towards the "ideal" weights, and hence each training case factored in is guaranteed. The resulting set of weights will be a compromise that equally balances the interests of all the training cases. Following is the actual code for a neuron to execute one training cycle:

```
Public Sub AutoTrain ()
Dim T as TrainingCase, Td as TrainingCaseDendrite
Dim ErrorTerm as Single
Const LearningRate as Single = 0.01
'Learn from each training case in this one cycle
For Each T in Me.TrainingCases
'Preset my dendrite's source axons' values to reflect
For Each Td in T.Dendrites
  Td.ForDendrite.FromNeuron.AxonValue = Td.Value
Next

'Given the training inputs, generate an output

Think ()
'Morph toward the desired output
ErrorTerm = T.AxonValue - Me.AxonValue
For Each Td in T.Dendrites
  Td.ForDendrite.Weight += Td.Value * ErrorTerm
    * LearningRate
Next
Next    End Sub
```

3.5 Back propagation

When researchers speak of learning in neural networks, they often refer to the concept of "back-propagation". Technically, the concept of giving each neuron its own training case is not back-propagation. In back-propagation, one would give training cases where the desired inputs would be for the input layer and the desired outputs would be for the output layer. All the layers would then go through a self-organizing process to figure out how best to achieve the goals of the training cases. Thus far, we have not reproduced this feat in our own sample program because this seems to be an area where things get complicated. Researchers refer in this realm to the problem of the network seeking a maximal level of fidelity but perhaps getting stuck during training in local maxima and never reaching their global maxima. We suspect this kind of problem gets magnified with each new hidden layer that's added. The potential richness of features increases, but the difficulty of getting training to work right may also.

3.6 Apen

The proposed system makes use of a single feature called ApEn for the epileptic detection. The ApEn is a time-domain feature that is capable of classifying complex systems [12]. An example of ApEn is shown in Fig 4.
The value of the ApEn is determined as shown in the following steps [13] [14].

1) Let the data sequence containing N data points be
$X = [x(1), x(2), x(3).... x(N)]$.

2) Let $\boldsymbol{x}(i)$ be a subsequence of X such that
$\boldsymbol{x}(i) = [x(i), x(i + 1), x(i + 2), . . . , x(i + m - 1)]$ for 1 $N - m$, where m represents the number of samples ≤ uise ≤d for the prediction.

3) Let r represent the noise filter level that is defined as

$$r = k \times \text{SD for } k = 0, 0.1, 0.2, 0.3. . . 0.9 \quad \textbf{(1)}$$

where SD is the standard deviation of the data sequence X

4) Let $\{\boldsymbol{x}(j)\}$ represent a set of subsequences obtained from $\boldsymbol{x}(j)$ by varying j from 1 to N. Each sequence $\boldsymbol{x}(j)$ in the set of $\{\boldsymbol{x}(j)\}$ is compared with $\boldsymbol{x}(i)$ and, in this process, two parameters, namely, $Cm\ i\ (r)$ and $Cm+1\ i\ (r)$ are defined as follows:

$$C^{m}_{i}(r) = \sum^{N-m}_{j=1} k_j / N-m \quad \textbf{(2)}$$

where $k = 1$, if $|\boldsymbol{x}(i) - \boldsymbol{x}(j)|$ for $1 \leq j \leq N - m$, $k = 0$, otherwise and

$$C^{m+1}{}_i(r) = \sum^{N-m}{}_{j=1} k_j / N\text{-}m \qquad \textbf{(3)}$$

With conditions depicted by (A) as shown at the bottom of the page

5) We define $\Phi m(r)$ and $\Phi m+1(r)$ as follows:

$$\Phi^m(r) = \sum^{N-m} i_{i=1} \ln (C^m{}_i\ (r)) / N\text{-}m \qquad \textbf{(4)}$$

$$\Phi^{m+1}(r) = \sum^{N-m} i_{i=1} \ln (C^{m+1}{}_i\ (r)) / N\text{-}m \qquad \textbf{(5)}$$

6) ApEn (m, r, N) is calculated using $\Phi^m(r)$ and $\Phi^{m+1}(r)$ as follows:

$$\text{ApEn}(m, r, N) = \Phi^m(r) - \Phi^{m+1}(r) \qquad \textbf{(6)}$$

$$[\sum^{N-m} i_{i=1} \ln (C^m{}_i\ (r)) / N\text{-}m] - [\sum^{N-m} i_{i=1} \ln (C^{m+1}{}_i\ (r)) / N\text{-}m] \qquad \textbf{(7)}$$

$$= 1/N\text{-}m\ [\sum^{N-m} i_{i=1} \ln (C^m{}_i\ (r)) - \sum^{N-m} i_{i=1} \ln (C^{m+1}{}_i\ (r))] \qquad \textbf{(8)}$$

$$= 1/N\text{-}m\ [\sum^{N-m} i_{i=1} \ln (C^m{}_i\ (r)) / C^{m+1}{}_i\ (r))] \qquad \textbf{(9)}$$

3.7 Pattern matching

Neuron should know something before explaining how they work in concert with other such neuron and when it recognizes the pattern “firing” takes place if the output is above some threshold which we choose 0.5. The only output (axon) for this neuron is always going to have a value between -1 and 1. Overall, we want to say that knowledge is encoded in the weights on the dendrites. The second most important lesson is that the output of this sort of thinking is "fuzzy". That is, the neuron compares input patterns and generates variable outputs that are higher the closer the inputs are to its archetypical pattern. So while there are definitive "match" (1) and "non-match" (-1) outputs, there is a whole range in between of somewhat matching.

4. Conclusion & Future work

Epilepsy is a common neurological disorder not a disease which is not contagious, fainting disorder and cause mental illness. Epileptic person has a tendency to have recurrent seizures which produces non linear dynamic system. By using Elman Neural Network and ApEn as an input feature for implementation of detection of epilepsy. Since, it is using a single input feature so that’s why we having low computational burden and best suited for the real-time detection of epileptic seizures. We described one kind of ANN and conception how to implement it.

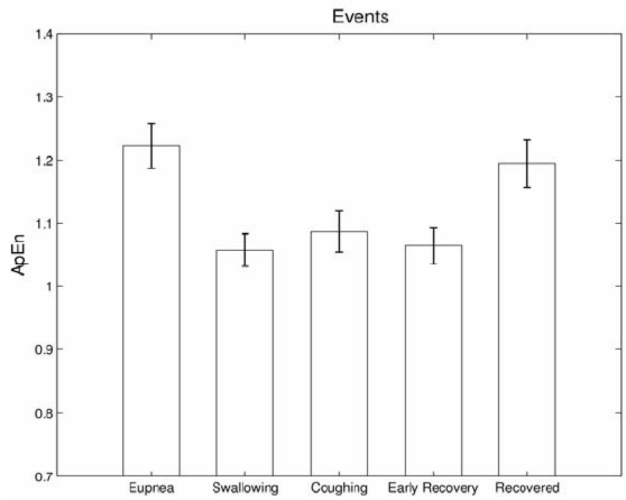

Fig 4. Approximate Entropy

By using probability NN which is a feed forward NN with two middle layers called radial basis and competitive layers [16], [17] Apen as an input feature, could also be used for implementation [1]. After then both networks performances can be calculated on the basis of sensitivity (SE), specificity (SP), and overall accuracy (OA) where

i) SE= (Total no. of correctly detected / Total no. of actual positive patterns) *100
ii) SP= (Total no. of correctly detected negative pattern / Total no. of actual negative pattern) * 100
iii) OA= (Total no. of correctly detected patterns / Total no. of applied patterns) * 100 [1].

And on the basis of this one can decide which network is best suitable for implementation. Secondly, one other interesting type uses linear inputs and outputs - values from -infinity to infinity - and can be used to learn to approximate linear and perhaps even nonlinear mathematical functions. These can be used to help control tricky manufacturing processes like chemical vapor deposition (CVD).

References

[1] Srinivasan et al, (2007). Approximate Entropy-based Automated Epileptic EEG detection using Artificial Neural Networks, [Online].

[2] N. Mc Grogan (1999) neural network detection of epileptic seizures in the electroencephalogram, [Online]. Available: http://www.new.ox.ac.uk/˜nmcgroga/work/transfer

[3] J. Gotman, "Automatic recognition of epileptic seizures in the EEG," Electroencephalogr. Clin. Neurophysiol. vol. 54, pp. 530–540, 1982

[4] A.M.Murro, D.W. King, J. R. Smith, B. B. Gallagher, H. F. Flanigin, and K. Meador, "Computerized seizure detection of complex partial seizures," *Electroencephalogr. Clin. Neurophysiol.* vol. 79, pp. 330–333, 1991.

[5] H. Qu and J. Gotman, "A patient-specific algorithm for the detection of seizure onset in long-term EEG monitoring: Possible use as a warning device," *IEEE Trans. Biomed. Eng.*, vol. 44, no. 2, pp. 115–122, Feb. 1997.

[6] S. Gigola, F. Ortiz, C. E. D' Attellis, W. Silva, and S. Kochen, "Prediction of epileptic seizures using accumulated energy in a multiresolution framework," *J. Neurosci. Methods*, vol. 138, pp. 107–111, 2004.

[7] W. Weng and K. Khorasani, "An adaptive structure neural network with application to EEG automatic seizure detection," *Neural Netw.*, vol. 9, pp. 1223–1240, 1996.

[8] J. Gotman and L. Wang, "State-dependent spike detection: Concepts and preliminary results," *Electroencephalogr. Clin. Neurophysiol.*, vol. 79, pp. 11–19, 1991.

[9] N. Pradhan, P. K. Sadasivan, and G. R. Arunodaya, "Detection of seizure activity in EEG by an artificial neural network: A preliminary study," *Comput. Biomed. Res.*, vol. 29, pp. 303–313, 1996.

[10] V. P. Nigam and D. Graupe, "A neural-network-based detection of epilepsy," *Neurol. Res.*, vol. 26, pp. 55–60, 2004.

[11] M. K. Kiymik, A. Subasi, and H. R. Ozcalik, "Neural networks with periodogram and autoregressive spectral analysis methods in detection of epileptic seizure," *J. Med. Syst.*, vol. 28, pp. 511–522, 2004.

[12] S. M. Pincus, I. M. Gladstone, and R. A. Ehrenkranz, "A regularity static for medical data analysis," *J. Clin. Monit.* vol. 7, pp. 335–345, 1991.

[13] J. Bruhn, H. Ropcke, and A. Hoeft, "Approximate entropy as an electroencephalographic measure of anesthetic drug effect during desflurane anesthesia," *Anesthesiology*, vol. 92, pp. 715–726, 2000.

[14] J. S. Richman and J. R. Moorman, "Physiological time-series analysis using approximate entropy and sample entropy," *Amer. J. Physiol.*, vol. 278, pp. H2039–H2049, 2000.

[15] Elman Neural Network, Available: http://en.wikipedia.org/wiki/Recurrent_neural_network.

[16] H. Demuth and M. Beale, *Neural Network Toolbox*. (For use with Matlab), Natick, MA: Math Works, 2000.

[17] C. J. Huang and W. C. Liao, "A comparative study of feature selection methods for probabilistic neural networks in cancer classification," in *Proc. 15th IEEE Intern. Conf. Tools with Artif. Intell. (ICTAI'03)*, Sacramento, CA, Nov. 3–5, 2003, pp. 451–458.

[18] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Phys. Rev. E, Stat. Nonlinear SoftMatter Phys.*, vol. 64, pp. 061907-1–061907-8, 2001.

[19] L. Diambra, J. C. Bastos de Figueiredo, and C. P.Malta, "Epileptic activity recognition in EEG recording," *Phys. A: Stat. Mech. Appl.*, vol. 273, pp. 495–505, 1999.

[20] Electroencephalogram, available at http://www.wikipedia.com

Dr. T. V. Prasad received his bachelors and masters degree in Computer Science from Nagarjuna University, AP India and doctoral degree from Jamia Milia Islamia, New Delhi, India. He has over 15 years of experience in industry and teaching. He has worked as Deputy Director in the Bureau of Indian Standards New Delhi. Currently he is Professor and Head of Department of Computer Sc. & Engg. at Lingaya's University, Faridabad, Haryana, India. He has 50 papers and four books to his credit. His areas of interest include bioinformatics artificial intelligence, consciousness studies, computer organization and architecture. He is a member of reputed bodies like ISRS, CSI, APBioNet, etc.

Ms. Mandeep Kaur received B. Tech and M. Tech in Computer Sc. & Engg. is working as Asst. Prof. (CSE) at Lingaya's University Faridabad, Haryana. She has more than 10 papers and guided many projects at graduate and post graduate level. Her areas of interest include Soft computing, Bio-Informatics, Software Engineering, Theory of computation/ Automata and computer organization and architecture

M. Gayatri is in Final year of bachelors at Lingaya's University, Faridabad, Haryana, India. Her areas of interest include Artificial Neural Networks, Software Development Life Cycle, Systems & Operations

Arun Kumar is in Final year of bachelors at Lingaya's University, Faridabad, Haryana, India. His areas of interest include Programming & Algorithm Designing, Computer Architecture, Artificial Neural Networks.

Manish Janghu is in Final year of bachelors at Lingaya’s University, Faridabad, Haryana, India. His areas of interest include Computer Organization, Operating Systems.