A Comparison of Genetic Algorithm & Neural Network (MLP) In Patient Specific Classification of Epilepsy Risk Levels from EEG Signals

Dr. (Mrs.) R.Sukanesh, R. Harikumar *Member, IAENG*

***Abstract*— This paper is aimed to compare the performance of a Genetic Algorithm (GA) and Multi- Layer Perceptron (MLP) Neural network in the classification of epilepsy risk level from Electroencephalogram (EEG) signal parameters. The epilepsy risk level is classified based on the extracted parameters like energy, variance, peaks, sharp and spike waves, duration, events and covariance from the EEG of the patient. A Binary Coded GA (BCGA) and MLP Neural network are applied on the code converter's classified risk levels to optimize risk levels that characterize the patient. The Performance Index (PI) and Quality Value (QV) are calculated for these methods. A group of ten patients with known epilepsy findings are used in this study. High PI such as 93.33% and 95.83% for BGA and MLP are obtained at QV of 20.14 and 21.59.**

***Index Terms*— EEG Signals, Epilepsy, Genetic Algorithm, Multi Layer Perceptron, Risk Levels**

I. Introduction

The recognition of specific waveforms and features in the Electroencephalogram (EEG) for classification of epilepsy risk levels has been the subject of much research. Techniques used are ranged from statistical methods to syntactic and knowledge based approaches. All of these methods require the definition of a set of features (or symbols and tokens) to be detected, and a pattern matcher to compare the observed values with the ideal, prototypical ones. An alternative approach, inspired by the configuration of the human brain, involves the use of artificial neural networks (ANN). One specific ANN architecture is the multilayer perceptron (MLP) feed-forward network with one or more layers between the input and output nodes (hidden layers). Training is achieved of MLP is achieved by the back propagation algorithm, which is a generalized least mean square algorithm. Most studies of ANNs in epilepsy are focused on spike and sharp wave form detection from EEG Signals.

This research focused on classification of epilepsy risk levels from EEG signals through ANNs and Genetic Algorithm (G.A). The GA is a type of natural evolutionary algorithm that models biological process to optimize highly complex cost functions by allowing a population composed of many individuals to evolve under specific rules to a state that maximizes the fitness. John Holland developed this method in 1975 [1]. Many researchers share the intuitions that if the space to be searched is large, is known not to be perfectly smooth and unimodal (i.e., consists of a single smooth 'hill'), or is not well understood, or if the fitness function is noisy, and if the task does not require a global optimum to be found, i.e., if quickly finding a sufficiently good solution is enough – a GA will have a good chance off being competitive with or surpassing other optimization methods [2]. A comparison of GA and MLP Network as a classification and optimization tools for bio medical engineers with a useful application of Epilepsy risk level classification is analyzed.

A. Background

The Electroencephalogram (EEG) is a measure of the cumulative firing of neurons in various parts of the brain. It contains information regarding changes in the electrical potential of the brain obtained from a given set of recording electrodes. These data include the characteristic waveforms with accompanying variations in amplitude, frequency, phase etc, as well as brief occurrence of electrical patterns such as spindles, sharps and spike waveforms. EEG patterns have shown to be modified by a wide range of variables including biochemical, metabolic, circulatory, hormonal, neuroelectric and behavioral factors. In the past, the encephalographer, by

Manuscript received on 18 TH July 2006

Dr. (Mrs.) R.Sukanesh, Professor & Division Head, Medical Electronics Division, Department of ECE, is with the Thiagarajar College of Engineering, Madurai, Tamil Nadu, 625015, India. (Phone: 91 452 2482240; fax: 91 452 2483427; e-mail: drsukanesh2003@yahoo.com).

R.Harikumar, Professor, Department of ECE, is with the Bannari Amman Institute of Technology-Sathyamangalam, & Research Scholar, Medical Electronics Division at Thiagarajar College of Engineering, Madurai, India. (Corresponding author Phone: 91 4295 221289; fax: 91 4295 22375; e-mail: harikumar_rajaguru@yahoo.com).

visual inspection was able to qualitatively distinguish normal EEG activity from localized or generalized abnormalities contained within relatively long EEG records. The most important activity possibly detected from the EEG is the epilepsy [6], [7]. Epilepsy is characterized by uncontrolled excessive activity or potential discharge by either a part or all of the central nervous system. The different types of epileptic seizures are characterized by different EEG waveform patterns [8].With real-time monitoring to detect epileptic seizures gaining widespread recognition, the advent of computers has made it possible to effectively apply a host of methods to quantify the changes occurring based on the EEG signals.

II. Materials and Methods

The EEG data used in the study were acquired from ten epileptic patients who had been under the evaluation and treatment in the Neurology department of Sri Ramakrishna Hospital, Coimbatore, India. A paper record of 16 channel EEG data is acquired from a clinical EEG monitoring system through 10-20 international electrode placing method. The EEG signal was band pass filtered between 0.5 Hz and 50Hz using five pole analog Butter worth filters to remove the artifacts. With an EEG signal free of artifacts, a reasonably accurate detection of epilepsy is possible; however, difficulties arise with artifacts. This problem increases the number of false detection that commonly plagues all classification systems. With the help of neurologist, we had selected artifact free EEG records with distinct features. These records were scanned by Umax 6696 scanner with a resolution of 600dpi.

Since the EEG records are over a continuous duration of about thirty seconds, they are divided into epochs of two second duration each by scanning into a bitmap image of size 400x100 pixels. A two second epoch is long enough to detect any significant changes in activity and presence of artifacts and also short enough to avoid any repetition or redundancy in the signal [1] [2] [3]. The EEG signal has a maximum frequency of 50Hz and so, each epoch is sampled at a frequency of 200Hz using graphics programming in C. Each sample corresponds to the instantaneous amplitude values of the signal, totaling 400 values for an epoch. The different parameters used for quantification of the EEG are computed using these amplitude values by suitable programming codes. The parameters are obtained for three different continuous epochs at discrete times in order to locate variations and differences in the epileptic activity. We used ten EEG records for both training and testing. These EEG records had an average length of six seconds and total length of 60 seconds. The patients had an average age of 31 years. A total of 480 epochs of 2 seconds duration are used. General features of the test records are as follows.

Record 1and 4: High risk level with peaks and spikes.

Record 3 and6: Patient under clinical observation after two weeks of intensive drug therapy.

Record 2and 8: Very High risk level with energy, Peaks and spikes.

Record 5and 7: Medium risk level with variance, energy, peaks and spikes.

Record 9and 10: Low risk level with variance, energy, peaks and spikes with occasional medium risk levels

A. *Feature Extraction and Code Converter System*

The various parameters obtained by sampling are given as inputs to the code converter system as shown in fig. 1. These parameters are defined as follows [9], [10], [11].

1. The energy in each two-second epoch is given by

$$E = \sum_{i=1}^{n} x_i^2 \quad (1)$$

Where x_i is signal sample value and n is number of samples. The normalized energy is taken by dividing the energy term by 1000.

2. The total number of positive and negative peaks exceeding a threshold is found

.3. Spikes are detected when the zero crossing duration of predominantly high amplitude peaks in the EEG waveform lies between 20 ms and 70 ms and sharp waves are detected when the duration lies between 70ms and 200ms.

4. The total numbers of spike and sharp waves in an epoch are recorded as events.

5. The variance is computed as σ given by

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n} \quad (2)$$

Where $\mu = \frac{\sum_{i=1}^{n} x_i}{n}$ is the average amplitude of the epoch.

6. The average duration is given by

$$D = \frac{\sum_{i=1}^{p} t_i}{p} \quad (3)$$

Where t_i is one peak to peak duration and p is the number of such durations.

7. Covariance of Duration which is defined as the variation of the average duration is

$$CD = \frac{\sum_{i=1}^{p}(D - t_i)^2}{pD^2} \quad (4)$$

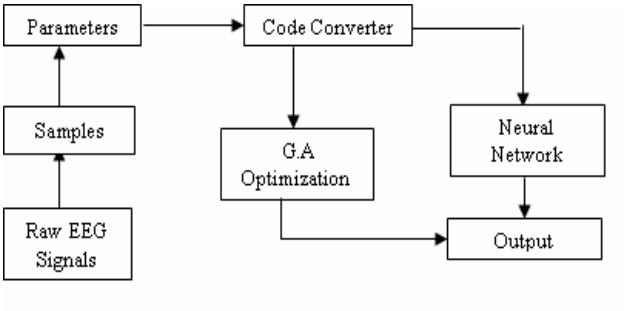

Fig.1.Block diagram of Genetic Algorithm and Neural network based Classification system

The average values of extracted parameters in each 2 seconds epoch over sixteen channels of the patient record 4 is listed in the Table I

Table I Average values of Extracted Parameters from Patient Record 4

Parameters	**Epoch1**	**Epoch2**	**Epoch3**
Energy	5.2869	8.581	10.10
Variance	1.1397	2.121	2.322
Peaks	1	2	2
Total	9	38	35
Sharp &Spike	8	6	6
Total	122	91	87
Events	12	10	10
Total	185	154	145
Average duration	3.798	4.042	3.883
Covariance	0.5793	0.5123	0.5941

With the help of expert's knowledge and our experiences with the references [12],[13],[14], we have identified the following parametric ranges for five linguistic risk levels (very low, low, medium, high and very high) in the clinical description for the patients which is shown in table II

Table II Parameter Ranges for Various Risk Levels

Risk levels / **Normalized Parameters**	**Normal**	**Low**	**Medium**	**High**	**Very high**
Energy	0-1	0.7-3.6	2.9-8.2	7.6-11	9.2-30
Variance	0-0.3	0.15-0.45	0.4-2.2	1.6-4.3	3.8-10
Peaks	0-2	1-4	3-8	6-16	12-20
Events	0-2	1-5	4-10	7-16	15-28
Sharp waves	0-2	1-5	4-8	7-11	10-12
Average Duration	0-0.3	0.15-0.45	0.4-2.4	1.8-4.6	3.6-10
Covariance	0-0.05	0.025-0.1	0.09-0.4	0.28-0.64	0.54-1

The output of code converter is encoded into the strings of seven codes corresponding to each EEG signal parameter based on the epilepsy risk levels threshold values as set in the table II The expert defined threshold values are containing noise in the form of overlapping ranges. Therefore we have encoded the patient risk level into the next level of risk instead of a lower level. Likewise, if the input energy is at 3.4 then the code converter output is at medium risk level instead of low level [12].

B. Code Converter as a Pre Classifier

The encoding method processes the sampled output values as individual code. Since working on definite alphabets is easier than processing numbers with large decimal accuracy, we encode the outputs as a string of alphabets. The alphabetical representation of the five classifications of the outputs is shown in table III.

Table III Representation of Risk Level Classifications

Risk Level	Representation
Normal	U
Low	W
Medium	X
High	Y
Very High	Z

The ease of operation in using characteristic representation is obviously evident than in performing cumbersome operations of numbers. By encoding each risk level one of the five states, a string of seven characters is obtained for each of the sixteen channels of each epoch. A sample output with actual patient readings is shown in fig. 2 for eight channels over three epochs. It can be seen that the Channel 1 shows low risk levels while channel 7 shows high risk levels. Also, the risk level classification varies between adjacent epochs**.** There are sixteen different channels for input to the system at three epochs.

This gives a total of

forty-eight input output pairs. Since we deal with known cases of epileptic patients, it is necessary to find the exact level of epilepsy risk in the patient. This will also aid towards the development of automated systems that can precisely classify the risk level of the epileptic patient under observation. Hence an optimization is necessary. This will improve the classification of the patient and can provide the EEGer with a clear picture [15].

The outputs from each epoch are not identical and are varying in condition such as [YYZXXXX] to [WYZYYYY] to [YYZZYYY]. In this case energy factor is predominant and this results in the high risk level for two epochs and low risk level for middle epoch. Channel five and six settles at high risk level. Due to this type of mixed state output we cannot come to proper conclusion, therefore we group four adjacent channels and optimize the risk level. The frequently repeated patterns show the average risk level of the group channels. Same individual patterns depict the constant risk level associated in a particular epoch. Whether a group of channel is at the high risk level or not is identified by the occurrences of at least one Z pattern in an epoch.

Epoch 1	Epoch 2	Epoch 3
WYYWYYY	WYYWYYY	WZYYWWW
YZZYXXX	YYYYXXX	YYYXYYY
YYZXYYY	YYYYYYY	YYYYYYY
YZZYXYY	XZZXYYY	YYYYYYY
ZZZYYYY	WYYYXXX	YYYXYYY
YYZXXXX	WYZYYYY	YZZYYYY
ZZZYYYY	YYYYYYY	ZZZYYYY
YYYYXXX	YYYYXXX	YYYXZYY

Fig. 2. Code Converters Output

The Code converter‘s classification efficiency is evaluated from the following parameters. The Performance of the Code converter is defined as follows [5],

$$PI = \frac{PC - MC - FA}{PC} \times 100 \quad (5)$$

Where PC – Perfect Classification, MC – Missed Classification, FA – False Alarm

The Performance of code converter is 40%.

The perfect classification represents when the physician agrees with the epilepsy risk level. Missed classification represents a High level as Low level. False alarm represents a Low level as High level with respect to physician’s diagnosis.

The sensitivity S_e and specificity S_p are defined as [17],

$S_e = [PC/(PC+FA)]*100$ (6)

(0.5/0.6)*100=83.33%

$S_p = [PC/(PC+MC)]*100$ (7)

(0.5/0.7)*100=71.42%

Due to the low values of performance index, sensitivity and specificity it is essential to optimize the out put of the code converter. In the following section we discuss about the GA based optimization of epilepsy risk levels.

III. Binary Coded Genetic Algorithm

GA has blossomed rapidly due to the easy availability of low cost but fast speed small computers. The complex and conflicting problems that required simultaneous solutions, which in past were considered deadlocked problems, can now be obtained with GA. However, the GA is not considered a mathematically guided algorithm. The optima obtained are evolved from generation to generation without stringent mathematical formulation such as the traditional gradient–type of optimizing procedure. Infact; GA is much different in that context. It is merely a stochastic, discrete event and a non linear process. The obtained optima are an end product containing the best elements of previous generations where the attributes of a stronger individual tend to be carried forward into the following generation. The rule of the game is “survival of the fittest will win” [3].

A simple genetic algorithm can be summed up in seven steps as follows [16]:

1. Start with a randomly generated population of n chromosomes
2. Calculate fitness of each chromosome
3. Select a pair of parent chromosomes from the initial population
4. With a probability P_{cross} (the ‘crossover probability’ of the ‘crossover rate’), perform crossover to produce two offspring
5. Mutate the two offspring with a probability P_{mut} (the mutation probability)
6. Replace the offspring in the population
7. Check for termination or go to step 2

Each iteration of the above steps is called a generation. The termination condition is usually a fixed number of generations typically anywhere from 50 to 500 or more. Under certain other circumstances, a check for global minimum is done after each generation and the algorithm is terminated as and when it is reached [4].The binary coded genetic algorithm (BCGA) is a type of genetic algorithm that works with a finite parameter space. This characteristic makes it ideal in optimizing a cost due to parameters that assume only finite number of values. In case of optimizing parameters that are continuous, quantization is applied. The chief aspect of this method is the representation of the parameter as strings of binary digits of 0 and 1. This composition allows simple crossover and mutation functions that can operate on the chromosomes.

A. Binary Representation

The five risk levels are encoded as Z>Y>X>W>U in binary strings of length five bits using weighted positional representation as shown in table IV. Encoding each output risk level gives us a string of seven chromosomes, the fitness of which is calculated as the sum of probabilities of the individual genes. For example, if the output of an epoch is encoded as ZZYXWZZ, its fitness would be 0.419352.

Table IV. Binary Representation of Risk Levels

Risk Level	Code	Binary string	Weight	Probability
Very High	Z	10000	16/31 = 0.51612	0.086021
High	Y	01000	8/31= 0.25806	0.043011
Medium	X	00100	4/31= 0.12903	0.021505
Low	W	00010	2/31= 0.06451	0.010752
Normal	U	00001	1/31= 0.03225	0.005376
		11111=31	Σ = 1	

B .Operation on Data

Using the above representation, we have developed a genetic algorithm that optimizes the output of the code converter and gives four risk level patterns in the five categories for each patient. This is obtained by the following procedure [16]

- Open three files having 16 strings each and process stage 1
- Divide into sets of 4 strings and iterate
  1) Maximum of 128 generations
  2) Two strings selected randomly
  3) Single point crossover after 3rd position with probability $P_{cross} = 0.75$
  4) Random mutation of any position to any state in the offspring with lower fitness and probability $P_{mut} = 0.150535$ which is the probability of XXXXXXX
  5) Best two strings with higher fitness get selected for next stage
- Stage 2 operates on 24 chromosomes with 8 from each epoch
- Divide into sets of 4 strings and iterate in same way as stage 1
- Output of stage 2 is 4 best strings in each epoch
- Final stage is row-wise optimization in which each row of the epochs are iterated and one best output is taken
- Last iteration involving string of each row gives the final 4 output strings

Table V. Optimization by Binary Genetic Algorithm

EPOCH3		
YYYXYZZ YYYXYZZ ZYYYZZY YYYXXZY YYYYYZY YYYXYYY YYYYYYY ZZYZZZZ YYYYYYY YYYXYYY YYYYYYY ZYYYYYY YYYYYYY YYYYXXX ZZYZZZZ ZZYZZZY	YYYYZZY YYYXYZZ YYYZZZY ZZYWYYY ZYYZYYY YYYZYYY ZZYZZZZ YYYZZZY	ZZYZYZY YYYZZZY YYYZZZY ZZYYYYZ
FINAL STAGE		

EPOCH1	EPOCH2	EPOCH3	FINAL 4
ZYYZYZZ YYYZZYY YYYXZZZ YYYYYZZ	ZYYZZZZ YYYZZZZ ZZYXZZZ ZZYYXZZ	ZZYZYZY YYYZZZY YYYZZZY ZZYYYYZ	ZZZYZZZ YYYYZZZ YZYYWWZ ZZZYYWW

By the application of the above procedure, the 48 risk level patterns obtained by the code converter are reduced to 4 risk level patterns, which define that of the patient. This process for a single patient is shown in table V. From the table V, each epoch is first reduced to 4 strings, which give the optimized risk levels of the epoch. An operation on the 12 strings in the final stage by a row-wise optimization gives the final 4 strings, representing the risk levels of the patient.

The drawback in this optimization as evident from the table V is that even though there are lower risk level states in the intermediate stage, they get omitted while proceeding to the final stage. This is because the algorithm takes only the higher fitness strings, which are the strings that represent the higher risk levels. Since we deal with only known cases of epilepsy, it can be stated that this is not a disadvantage, as those states will result in false alarms, which are defined later. It can also be inferred from the table IV that the mutation taking place in the initial stages affects the final result in only a small extent. Also, the final four strings which are obtained as the risk levels of the patient matches with the initial strings to a large extent. These advantages of the algorithm outline its use for the optimization of the risk levels of epilepsy. The optimization of epilepsy risk levels using MLP neural network is analyzed in the following section of the paper.

IV. Multi Layer Perceptrons (MLP) Neural Network for Risk Level Optimization

`Guoqiang (2000) listed out the advantages of the neural networks in the following theoretical aspects [26].First, neural networks are data driven self-adaptive methods in that they can adjust themselves to the data without any explicit specification

of functional or distributional form for the underlying model. Second, they are universal functional approximators in that neural networks can approximate any function with arbitrary accuracy. Third, neural networks are a nonlinear model, which makes them flexible in modeling real world complex relationships. Finally, neural networks are able to estimate the posterior probabilities, which provide the basis for establishing classification and performance.

The primary aim of developing an ANN is to generalize the features (epilepsy risk level) of the processed code converters outputs. We have applied different architectures of MLP networks for optimization. The simulations were realized by employing Neural Simulator 4.0 of Matlab v.7.0 [24]. Since our neural network model is patient specific in nature, we are applying 48 (3x16) patterns for each MLP model. There are ten models for ten patients. As the number of patterns in each database for training is limited, each model is trained with one set of patterns (16) for zero mean square error condition and tested with other two sets of patterns (2x16). After network is trained using these, the classification performance of test set is recorded. The testing process is monitored by the Mean Square Error (MSE) which is defined as [19]

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(O_i - T_j)^2 \tag{9}$$

Where Oi is the observed value at time i, T_j is the target value at model j; j=1-10, and N is the total number of observations per epoch and in our case, it is 16. As the number of hidden units is gradually increased from its initial value, the minimum MSE on the testing set begins to decrease. The optimal number of hidden units is that number for which the lowest MSE is achieved. If the number of hidden units is increased beyond this performance does not improve and soon begins to deteriorate as the complexity of the neural network model is increased beyond that which is required for the problem. Multilayer perceptrons (MLPs) are feed forward neural networks trained with the standard back propagation algorithm [20]. To reduce the training time, an advanced NN training algorithm, called Levenberg-Marquardt (LM) is used. This training algorithm is based on the Gauss-Newton method, and it reduces the training time dramatically. It provides a fast convergence, it is robust and simple to implement, and it is not necessary for the user to initialize any strange design parameters. It out performs simple gradient descent and other conjugate gradient methods in a wide variety of problems [21].

For a standard back propagation algorithm, we used an approximate steepest descent rule and updated the weight according to the following equation:

$$W(k+1) = W(k) + \alpha\frac{\partial E(k)}{\partial W(k)} + \mu\Delta W(k) \tag{10}$$

Where W (k) is the weight at the k th iteration, α is the learning rate, (k) is the difference between NN output and the expected output. ΔW (k) is the weighted difference between the k th and (k-1) th iteration (this item is optimal), and μ is the momentum constant. In some adaptive algorithms, α change with time, but this requires many iterations and leads to a high computational burden. Fortunately, the non-linear least squares Gauss- Newton has been used to solve many supervised NN training problem. When Gauss-Newton update rule is employed to batch training, the solution provides iteratively as [25]:

$$W(k+1) = W(k) + \Delta W(k), k = 0,1,... \tag{11}$$

Where W(k) denotes the NN weight vector at the kth iteration and ΔW(k) is the changed weight. ΔW(k)is computed from:

$$\min\left\| J(k)\Delta W(k) + e(k)\right\| \tag{12}$$

ie., $J(k)^T J(k)\,\Delta W(k) = -J(k)^T e(k)$ (13)

Where $J(k) = \left[\frac{\partial ei(K)}{\partial Wj(k)}\right]$

Where $\|.\|$ is the Euclidean norm.

$e(k)=[e_1'(k),\ldots e_m'(k)]^T$ with $e_i'(k)=y_i'(k)- t_i'(k)$; (14)

and $W(k)=[w^1(1,1)\quad w^2(1,2)\ldots\quad w^1(S1,R)\quad b^1(1)\ldots b^1(s1)\ w^2(1,1)\ldots b^M(SM)]^T$ (15)

The above derivation is the essence of the Gauss-Newton algorithm. However, the Gauss-Newton is generally not locally convergent on problems that are very nonlinear or have very large residuals. To improve upon this situation, the following formula is usually adopted:

$$(J(k)^T J(k)+\mu S^T S)\Delta W(k) = -J(k)^T e(k) \tag{16}$$

Where $S \in R^{nxn}$ is a non singular matrix and μ is a coefficient. The searching direction obtained from this formula varies as μ changes. The Levenberge-Marquardt algorithm is based on this method and replaces S with the identity matrix and update weights can be obtained. The results of the MLP back propagation neural models trained with the Levenberg-Marquardt (LM) learning algorithm are shown in table VI. For all the models, the maximum number of inputs is (1x16) and the number of output is one, corresponding to the optimized risk level pattern. Taking into account the problem under consideration, ANN architectures with three layers were used, as these models have been documented as able to draw the boundaries of arbitrarily complex decision regions. The number of weights, the gain or learning rate η (0.3), momentum α (0.5), and training epochs are tabulated for each model. During the training phase, an error measure (9) of the closeness of the weights to a solution can be calculated for each pattern (16 input feature patterns) that represents a subject in the training set. This measure is used for determining whether a certain subject has been learned by the system.

Table VI. Estimation of MSE in Various MLP Network

Architectures

Architecture	Training Epochs	Mean Square Error (MSE) Index	
		Training	Testing
16-16-1	38	0	7.31E-03
16-3-1	6	0	2.19E-02
8-8-1	283	0	9.13E-03
8-4-1	6	0	5.1E-02
4-4-1	9	0	2.83E-08
4-4-4	12	0	7.74E-03
2-2-2	3820	3.0E-08	3.7 E-08
2-2-1	7	0	0
1-1-1	4538	1.08E-08	1.2E-08

In the MLP networks testing MSE index and number of epochs used for training are inversely proportional to each other. Therefore a compromise between them was achieved by taking into the consideration of larger training cost will ruin the system even though considerable accuracy is achieved in the targets (epilepsy risk levels) [22],[23]. Therefore we had selected 4-4-1 MLP network architecture which requires lesser number of training epochs and the same is depicted in the fig. 3.

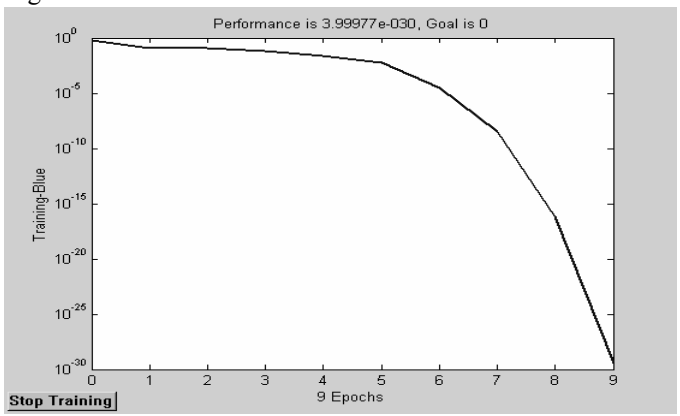

Fig. 3. Training of MLP Feed forward Neural Network (4-4-1)

V. Results and Discussions

The outputs are obtained for three epochs for every patient in classifying the epileptic risk level by the code converter, Genetic algorithm, and MLP neural network approaches. To study the relative performance of these systems, we measure two parameters, the Performance Index and the Quality Value. These parameters are calculated for each set of the patient and compared.

A. Performance Index

The PI calculated for the aforesaid classification methods are illustrated in table VII using (5)

Table VII. Performance Index

Methods	Perfect Classification	Missed Classification	False Alarm	Performance Index
Code converter	50	20	10	40
BCGA optimization	93.75	0	6.25	93.33
MLP Optimization	95.83	0	4.16	95.65

It is evident that the optimizations give a better performance than the code converter techniques due to its lower false alarms and missed classifications. For code converter classifier we have max detection of 50% with false alarm of 10% .Similarly for BCGA and MLP Neural network optimizations we obtained perfect detections of 93.75%and 95.83% with false alarms of 6.25% and 4.16%. This shows that the BCGA and MLP neural network classifiers are performing better than the single code converter classifier.

B. Quality Value

The goal of this paper is to classify the epileptic risk level with as many perfect classifications and as few false alarms as possible. In Order to compare different classifiers we need a measure that reflects the overall quality of the classifier [15].Their quality is determined by three factors, Classification rate, Classification delay, and False Alarm rate.

The quality value Q_V is defined as [5],

$$Q_V = \frac{C}{\left(R_{fa} + 0.2\right) * \left(T_{dly} * P_{dct} + 6 * P_{msd}\right)} \quad (17)$$

Where, C is the scaling constant,

R_{fa} is the number of false alarm per set

T_{dly} is the average delay of the on set classification in seconds

P_{dct} is the percentage of perfect classification and

P_{msd} is the percentage of perfect risk level missed.

A constant C is empirically set to 10 because this scale is the value of Q_V to an easy reading range. The higher value of Q_V, the better the classifier among the different classifier, the classifier with the highest Q_V should be the best. The two different approaches give different results. Hence a comparative study is needed whereby the advantages of one over the other can be easily validated and the best method found out. A study of code converter method without and with BCGA optimization was performed and their results were taken as the average of all ten known patients was tabulated in table VIII.

Table VIII. Results of Classifiers Taken As Average of All Ten Patients

Parameters	Code Converter Method Before Optimization	Binary Coded Genetic Algorithm	MLP Neural Network
Risk level classification rate (%)	50	93.75	95.83
Weighted delay (s)	4	0.492	0.463
False-alarm rate/set	0.2	0.0625	0.0416
Performance Index %	40	93.33	95.65
Quality value	6.25	20.14	21.59

VI. Conclusion

This paper aims at classifying the epilepsy risk level of epileptic patients from EEG signals. The parameters derived from the EEG signal are stored as data sets. Then the code converter technique is used to obtain the risk level from each epoch at every EEG channel. The goal was to classify perfect risk levels with high rate of classification, a short delay from onset, and a low false alarm rate. Though it is impossible to obtain a perfect performance in all these conditions, some compromises have been made. As a high false alarm rate ruins the effectiveness of the system, a low false-alarm rate is most important. Genetic algorithm and Neural network (MLP) optimization techniques are used to optimize the risk level by incorporating the above goals. The spatial region of normal EEG is easily identified in this classification method. The major limitation of GA method is that if one channel has a high-risk level, then the entire group will be maximized to that risk level. This will affect the non-epilepsy spike region in the groups and for NN its additional training cost involves in the learning procedures of the network. However, the classification rate of epilepsy risk level of above 90% is possible in our method. The missed classification is almost 0% for a short delay of 2 seconds. The number of cases from the present ten patients has to be increased for better testing of the system. From this method we can infer the occurrence of High-risk level frequency and the possible medication to the patients. Also optimizing each region's data separately can solve the focal epilepsy problem. This risk level classification of diabetic epileptic patients may also be taken as further extension of this paper.

VII. Acknowledgement

The authors thank the Management and Principal of Bannari Amman Institute of Technology, Sathyamangalam, and the Management of Thiagarajar College of Engineering, Madurai for providing excellent computing facilities and encouragement. The authors are grateful to Dr.Asokan, Neurologist, Ramakrishna Hospital Coimbatore and Dr. B.Rajalakshmi, Diabetologist, Govt. Hospital Dindigul for providing the EEG signals.

References

[1] K.F. Man , "Genetic Algorithms: Concepts and Applications", *IEEE Transactions on Industrial Electronics*, vol,43no,5 October 1996, pp 519 – 533.

[2] Randy L. Haupt and Sue Ellen Haupt, *"Practical Genetic Algorithms"*, John Wisely and Sons, 1998.

[3] D.E.Goldberg, *"Genetic Algorithms in Search, Optimization and Machine Learning"*, Reading, MA: Addison-Wesley, 1989.

[4] Melanie Mitchell, *"An Introduction to Genetic Algorithms"*, A Bradford Book MIT Press, 1997.

[5] Alison A Dingle, "A Multistage system to detect epileptic form activity in the EEG", *IEEE Transactions on Biomedical Engineering, vol*, 40, no, 12, December 1993, pp 1260-1268.

[6] Mark van Gils, 'Signal processing in prolonged EEG recordings during intensive care", *IEEE EMB Magazine,* vol, 16,no,6, November/December 1997, pp 56-63.

[7] Haoqu and Jean Gotman, "A patient specific algorithm for detection onset in long-term EEG monitoring-possible use as warning device", *IEEE Transactions on Biomedical Engineering* vol,, 44,no2, February 1997,pp 115-122.

[8] Arthur C Gayton, *"Text Book of Medical Physiology"*, Prism Books Pvt. Ltd., Bangalore, 9th Edition, 1996.

[9] Seunghan Park , "TDAT Domain Analysis Tool for EEG Analysis", *IEEE Transactions on Biomedical Engineering,* vol,37,no,8, August 1990,pp 803-811.

[10] Yuhui Shi , "Implementation of Evolutionary Fuzzy systems", *IEEE Transactions on Fuzzy Systems*, vol,7,no,2, April 1999, pp 109-119.

[11] R.Neelaveni and G.Gurusamy, "EEG Signal Analysis Methods – A Review*", Proceedings of National System Conference NSC-98,* , 1998, pp. 355-361.

[12] R.Harikumar and B.Sabarish Narayanan, "Fuzzy Techniques for Classification of Epilepsy risk level from EEG Signals", *Proceedings of IEEE TENCON– 2003,* Bangalore, India, 14-17 October 2003, pp 209-213.

[13] R.Harikumar, "Epilepsy Detection From EEG Signals – A Statistical Approach", *Proceedings of ICECON'03*, NIT Trichy, 5 – 6 December 2003.

[14] P.Aravindan Bharathi and V.Beena, "Analysis of Statistical Tests and Fuzzy Techniques in Diagnosis of Epilepsy from EEG signals", *Proceedings of ICSCI 2004, Hyderabad,* 12 – 15 February 2004, pp 131 – 137.

[15] Ching-Hung Wang, "Integrating Fuzzy Knowledge by Genetic Algorithms", *IEEE Transactions on Evolutionary Computations*, vol,2,no,4, November 1998, pp 138 – 149.

[16] Marco Russo, "Fu Ge Ne Sys – A Fuzzy Genetic Neural System for Fuzzy Modeling", *IEEE Transactions on Fuzzy Systems*, vol,6,no,3 ,August 1998, pp 373 – 387.

[17] Rangaraj M. Rangayyan, *"Bio- Medical Signal Analysis A Case Study Approach"*, IEEE Press-John Wiley &sons Inc New York 2002.

[18] Horn, J.Goldberg, D.E and Deb,K. "*Long path problems"*. In Y.Davidor, H.P.Schwefel and R.Männer (Eds.), *Lecture Notes in Computer Science 866-Parallel Problem Solving from Nature-PPSNIII, International Conference on Evolutionary Computation, The Third Conference on Parallel Problem Solving from Nature*, 1994,pp 149-158.

[19] Nurettin Acir etal., " Automatic Detection Of Epileptiform Events In EEG By A Three- Stage Procedure Based on Artificial Neural Networks ",*IEEE transaction on Bio Medical Engineering* ,vol.52,no.1,January 2005, pp 30-40.

[20] Drazen.S.etal., "Estimation of difficult –to- Measure process variables using neural networks", *Proceedings of IEEE MELECON-2004*, 2004, pp 37-390.

[21]. Moreno.L.etal., "Brain Maturation Estimation Using Neural Classifier," *IEEE Transaction of Bio Medical Engineering*, vol.42, no.2,1995, pp 428-432.

[22]. Tarassenko.L, Y.U.Khan, M.R.G.Holt, "Identification Of Inter-Ictal Spikes in the EEG Using Neural Network Analysis," *IEE Proceedings–Science Measurement Technology*,vol.145,no.6,1998, pp 270-278.

[23]. Yuan-chu Cheng, Wei-Min Qi,WeiYou Cai, "Dynamic Properties of Elman And Modified Elman Neural Network," *Proceedings of IEEE, First International Conference on Machine Learning And Cybernetics*, Beijing,2002,pp.637-640.

[24] H.Demuth and M.Beale, "*Neural Network Tool Box: User's Guide, Version 3.0*,"The Math Works, Inc., Natick, MA, 1998.

[25] Li Gang etal, "An Artificial –Intelligence Approach to ECG Analysis," *IEEE EMB Magazine*,vol 20, 2000, pp 95-100.

[26] Guoqiang Peter Zhang , "Neural Networks for Classification: A Survey," *IEEE Transaction on Systems, Man And Cybernetics-Part C*, vol.30 No.4, November 2000, pp 451- 462.

Dr. (Mrs.) R.Sukanesh

Dr.(Mrs.).R.Sukanesh received her bachelor's degree in ECE from Government College of Technology Coimbatore in1982. She obtained her M.E (Communication Systems) degree from PSG College of Technology, Coimbatore in 1985 and PhD in Bio Medical Engineering from Madurai Kamaraj University, Madurai in 1999.Since 1985 she is working as a faculty in the Department of ECE at Thiagarajar College of Engineering, Madurai and presently, she is Professor of ECE and Heads the Medical Electronics Division in the same College. Her main research area includes Biomedical Instrumentation, Neural Networks, Bio Signal Processing and Mobile Communication. She is guiding twelve PhD theses in these areas. She has published several papers in International and National Journals and also published around sixty papers in International and National Conferences conducted both in India and abroad. She has delivered a number of invited lectures in various Universities. She has a Diploma in Higher Learning and has co authored a book on ***Gandhian Thoughts.*** She is life member of Bio medical Society of India, Indian Association of Bio medical Scientist and ISTE.

R.Harikumar

R.Harikumar received his B.E (ECE) degree from REC Trichy in 1988.He obtained his M.E (Applied Electronics) degree from College of Engineering, Guindy, Anna university Chennai in 1990. He has 15 years of teaching experience at college level. He worked as faculty in the Department of ECE at PSNA College of Engineering & Technology, Dindigul. He was Assistant Professor in IT at PSG College of Technology, Coimbatore. He also worked as Assistant Professor in ECE at Amrita Institute of Technology, Coimbatore. Currently, he is Professor of ECE, Bannari Amman Institute of Technology, Sathyamangalam and he is pursuing doctoral programme in Bio-Medical Engineering under guidance of **Dr. (Mrs.) R.Sukanesh** at Department of ECE, Thiagarajar College of Engineering, Madurai. He has published twelve papers in International and National Journals and also published around thirty papers in International and National Conferences conducted both in India and abroad. His area of interest is Bio signal Processing, Soft computing, VLSI Design and Communication Engineering. He is life member of IETE and ISTE.