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A Patient Specific Neural Networks (MLP) for Optimization of Fuzzy Outputs in Classification of Epilepsy Risk Levels from EEG Signals

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Abstract— **In recent years Neural Networks have been widely used as pattern and statistical classifiers in bio medical engineering. Most research to date using hybrid systems (Fuzzy-Neuro) focused on the Multi-Layer Perceptron (MLP). Here we focus on MLP network as an optimizer for classification of epilepsy risk levels obtained from the fuzzy techniques using the EEG signal parameters. The obtained risk level patterns from fuzzy techniques are found to have low values of Performance Index (PI) and Quality Value (QV). The neural networks are trained and tested with 480 patterns extracted from three epochs of sixteen channel EEG signals of ten known epilepsy patients. Different architectures of MLP network was compared based on the minimum Mean Square Error (MSE), the better MLP network (2-4-2) were selected. The MLP network out performs the fuzzy techniques with high Quality Value (QV) of 25 when compared to low QV of 6.25**.

Index Terms— **EEG Signals, Epilepsy, Fuzzy Logic, Multilayer Perceptron Neural Networks, Risk Levels**

I. INTRODUCTION

Epilepsy, a disease known from ancient times, was believed to be “given by the Gods” and it is now considered as a window to the brain’s anatomy and function and is, therefore, an increasingly active interdisciplinary field of research. The highest incidence of epilepsy occurs in infant and in the elderly. This is due to genetic abnormalities, developmental anomalies, febrile convulsions, as well as brain craniofacial trauma, central nervous system infections, hypoxia, ischemia and tumors [1]. The hallmark of epilepsy is recurrent seizures. The seizures are due to sudden development of synchronous neuronal firing in the cerebral cortex and are recorded by electrodes on the scalp. Electroencephalographic (EEG) recordings from the epileptic brain show that these discharges may begin locally in portions of the cerebral hemispheres. Generalized seizures cause altered consciousness at the onset and are associated with a variety of motor symptoms, ranging from brief localized body jerks to generalized tonic-clonic activity. Seizures come and go, in a seemingly unpredictable way. In some patients, seizures can occur hundreds of times per day; in rare instances, they occur only once every few years.

The Electroencephalogram (EEG) is a recording of the electrical potentials generated by the brain. Typically, sixteen channels of data are recorded by measuring the potential difference between pairs of electrodes placed on the scalp [2]. EEG recording is a routine clinical procedure that provides information pertinent to the diagnosis of a number of brain disorders, particularly epilepsy. Between seizures, the EEG of a patient with epilepsy may be characterized by occasional epileptic form transients-spikes and sharp waves [3]. EEG patterns have shown to be modified by a wide range of variables including biochemical, metabolic, circulatory, hormonal, neuroelectric and behavioral factors [4]. In the past, the Encephalographer, by visual inspection was able to qualitatively distinguish normal EEG activity from localized or generalized abnormalities contained within relatively long EEG records. The different types of epileptic seizures are characterized by different EEG waveform patterns [5]. 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 [6]. In this paper, we compare the performance of three different Multi Layer Perceptron (MLP) neural networks in optimizing the epileptic risk level of the patient classified by the fuzzy system. We also present a comparison of these methods based on their performance indices and quality values.

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, Combiatore, 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

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EEG signal free of artifacts, a reasonably accurate detection of epilepsy is possible; however, difficulties arise with artifacts. 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 [7],[8]. 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 one minutes. The patients had an average age of 31 years. A total of 480 epochs of 2 seconds duration are used.

A Fuzzy System as a Pre Classifier

Neuro-Fuzzy classification system is shown in figure 1. The main objective of this research is to classify the epilepsy risk level of a patient from EEG signals. This is accomplished as:

1) Fuzzy classification for epilepsy risk level at each channel from EEG signals and its parameters.
2) Each channel results are optimized, since they are at different risk levels.
3) Performances of fuzzy classification before and after the MLP neural networks (supervised) optimization methods are analyzed.

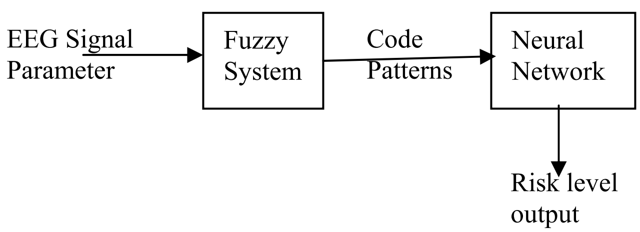

Fig.1. Neuro - Fuzzy Classification System

The parameters derived from EEG signals are [4] [5] [6],
1. The energy in each two-second epoch is given by

$$E = \sum_{i=1}^{n} x_i^2 \tag{1}$$

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 and 70 ms and sharp waves are detected when the duration lies between 70 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

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

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

6 .The average duration is given by $D = \frac{\sum_{i=1}^{p} t_i}{p}$ (3)

Where t_i is one peak to peak duration and p is the number of such durations.
7. Covariance of Duration .The variation of the average duration is defined by $CD = \frac{\sum_{i=1}^{p}(D - t_i)^2}{pD^2}$ (4)

B. Fuzzy Membership functions

The energy is compared with the other six input features to give six outputs. Each input feature is classified into five fuzzy linguistic levels viz., *very low, low, medium, high* and *very high* [9],[10]. The triangular membership functions are used for the linguistic levels of energy, peaks, variance events, spike and sharp waves, average duration and covariance of duration. The output risk level is classified into five linguistic levels namely *normal, low, medium, high* and *very high.*

C. Fuzzy Rule Set

Rules are framed in the format

IF Energy is low AND Variance is low THEN Output Risk Level is low

In this fuzzy system we have five linguistic levels of energy and five linguistic levels of other six features such as variance, peaks, events, spike and sharp waves, average duration and covariance of duration. Theoretically there may be 5^6 (that is 15625) rules are possible but we had considered the fuzzy pre -classifier as a combination of six two inputs and one output (2×1) system. With energy being a constant one input the other input is selected in sequential manner. This two inputs one output (2×1) fuzzy system works with 25 rules. We obtain a total rule base of 150 rules based on six sets of 25 rules each. This is a type of fuzzy rule based system [11].

D. Estimation of Risk Level in Fuzzy Outputs

The output of a fuzzy logic represents a wide space of risk levels. This is because 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 risk the patient. This will also aid in the development of automated systems that can precisely classify the risk level of the epileptic patient under observation. Hence an optimization of the outputs of the fuzzy system is necessary. This will improve the classification of the patient and can provide the EEGer with a clear picture. A specific coding method processes the output fuzzy values as individual code. The alphabetical representation of the five risk level classifications of the outputs is shown in table .I

Table .I Representation of Risk level Classifications

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

A sample output of the fuzzy system with actual patient readings is shown in fig. 2 for eight channels over three epochs. It can be seen that the Channel 1 shows medium and high risk levels while channel 8 shows very high risk levels. Also, the risk level classification varies between adjacent epochs.

Epoch 1	**Epoch 2**	**Epoch 3**
YYYYXX	**ZYYWYY**	**YYYXYZ**
YYYXXY	**ZZYZZZ**	**YYYXYZ**
YYYYYY	**ZZYZZZ**	**ZYYYZZ**
ZYYYZZ	**ZZYZYY**	**YYYXXZ**
YYYYYY	**YYYXYY**	**YYYYYZ**
YYYYYY	**YYYXYY**	**YYYXYY**
YYYYYY	**YYYYYY**	**YYYYYY**
ZZYZYZ	**ZZYZZZ**	**ZZYZZZ**

Fig. 2. Fuzzy Logic Output

The Performance of the Fuzzy method is defined as follows [5]

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

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

= [(0.5-0.2-0.1)/0.5] *100 =40%

The perfect classification represents when the physicians and fuzzy classifier agrees with the epilepsy risk level. Missed classification represents a true negative of fuzzy classifier in reference to the physician and shows High level as Low level. False alarm represents a false positive of fuzzy classifier in reference to the physician and shows Low level as High level. The performance for Fuzzy classifier is as low as 40%. It is essential to optimize the out put of the fuzzy systems. We employed different architectures of MLP neural networks (post classifier) [12] to optimize the epilepsy risk level. A pertinent explanation for the neural network optimization is given below.

III. ROLE OF NEURAL NETWORKS IN THE OPTIMIZATION OF FUZZY OUTPUTS

Neural networks have been touted as having excellent potential for improving classification accuracy in patient specific diagnostic data. However, there have been few studies which have demonstrated these potential using real data sets [13]. The appeal of neural networks as pattern recognition systems is based upon several considerations. First, neural networks appear to perform as well or better than other techniques, and require no assumptions about the explicit parametric nature of distributions of the pattern data to be classified. In this regard they are similar to K-nearest neighbor algorithms. However, neural networks, once trained, are computationally more efficient.

A. Multi layer Perceptrons (MLP) Neural Network for Risk Level Optimization

Multilayer perceptrons (MLPs) are feed forward neural networks trained with the standard back propagation algorithm. They are supervised networks so they required a desired response to be trained [14]. They learn how to transform input data into a desired response, so they are widely used for pattern classification. Most NN applications involve MLPs. They are very powerful pattern classifiers. With one or two hidden layers they can approximate virtually any input-output map. They have been shown to approximate the performance of optimal statistical classifiers in difficult problems. They can efficiently use the information contained in the input data. The advantage of using this network resides in its simplicity and the fact that it is well suited for online implementation [15]. The Levenberg-Marquardt (LM) algorithm is the standard training method for minimization of MSE (Mean Square Error) criteria, due to its rapid convergence properties and robustness. 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. The LM algorithm is first shown to be a blend of vanilla gradient descent and Gaussian Newton iteration. This error back propagation algorithm is used to calculate the weights updates in each layer of the network. The LM update rule is given as[16]

$$\Delta W = \left(J^{T} J + \mu\right)^{-1} J^{T} e \qquad (6)$$

Where J is jacobian matrix of derivatives of each error to each weighted μ is a scalar, and e is error vector. If scalar μ is very large, the above method approximates gradient –descent. While if it is small the above expression becomes Gauss-Newton method. Because the GN method is faster but tends to less accurate near an error minima. The scalar μ is adjusted just like adaptive learning rate used by *trainbpx*. As long as the error gets smaller, μ is made smaller. Training continues until the error goal is met, the minimum error gradient occurs, the maximum value of μ occurs or the maximum number of epochs has finished.

B. Training and Testing Procedures for the Selection of Optimal Architecture

The primary aim of developing an ANN is to generalize the features (epilepsy risk level) of the processed fuzzy outputs. We have applied different architectures of MLP networks for optimization. The weights between input layer, the hidden layer and output layer network are trained with error back propagation algorithm to minimize the square output error to zero. The simulations were realized by Neural Simulator 4.0 of Matlab v.7.0 [17]. 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 [17]

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(O_i - T_j)^2 \qquad (7)$$

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. The training procedure for MLP Neural network is shown in the figure.3.

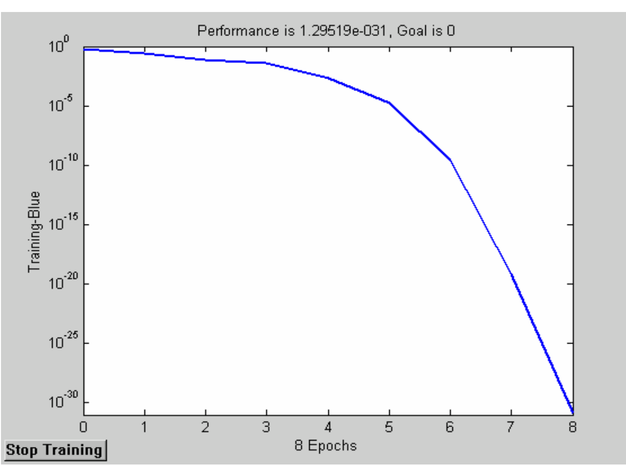

Fig. 3.Training of MLP Feed forward Neural Network (2-4-2)

The results of the MLP back propagation neural models trained with the Levenberg-Marquardt (LM) learning algorithm are shown in table 3. The gain or learning rate η (0.3), momentum α (0.5), and training epochs are tabulated for each model [18]. During the training phase, an error measure (7) 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. The squared error (e_i^2) from equation (7) between the input and the output of the ANN is converted into the confidence score using relation **C_i=exp (-λe_i^2)** where refers to the neural network index [19]. In this paper we have chosen λ=1. The average confidence score for each MLP Network architecture is tabulated in the table.II

Table II Estimation of MSE in Various MLP Network Architectures

Architecture	**Training Epochs**	**Mean Square Error (MSE) Index**		**Confidence score**
		Training	**Testing**	**$C_i=\exp(-\lambda e_i^2)$**
16-16-1	**38**	**0**	**7.31E-03**	**0.9927**
16-3-1	6	0	2.19E-02	0.9783
8-8-1	283	0	9.13E-03	0.9909
8-4-1	6	0	5.1E-02	0.9503
4-4-1	**9**	**0**	**2.83E-08**	**0.9999**
4-4-4	12	0	7.74E-03	0.992
2-2-2	3820	3.0E-08	3.7 E-08	0.9999
2-4-2	**8**	**0**	**0**	**1**
1-1-1	4538	1.08E-08	1.2E-08	0.9999

In the MLP networks testing procedures 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). Therefore we had selected (16-16-1),(4-4-1) and (2-4-2) MLP network architectures due to their lesser number of training epochs.

IV. RESULTS AND DISCUSSIONS

The outputs are obtained for three epochs for every patient and then the epileptic risk level is classified by the neural network approach. 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. The performance index (5) obtained by Fuzzy techniques and MLP (16-16-1),(4-41)&(2-4-2) neural network optimization are 40% , 96.29%, 99.34% and 100%respectively. The following table III shows the epilepsy risk level estimation for ten patient's specific MLP Feed forward networks at three different architectures.

Table III Estimation of MSE at Ten Patient Specific MLP (16-16-1),(4-4-1) &(2-4-2)Feed forward Neural Networks

Model	**Target Code**	**MLP Neural Network 16-16-1**		**MLP Neural network 4-4-1**		**MLP Neural network 2-4-2**	
		Test risk level Code	**Mean square Error(MSE)**	**Test risk level Code**	**Mean square Error(MSE)**	**Test risk level Code**	**Mean square Error(MSE)**
1.	ZZYZZZ	ZZ**Z**ZZZ	3.831E-03	ZZYZZZ	0	ZZYZZZ	0
2.	YYYXYY	**ZZ**YXYY	9.34E-03	YYYXYY	0	YYYXYY	0
3	YYYYYY	**Z**YY**Z**YY	7.32E-03	YYYYYY	0	YYYYYY	0
4	YYXXYY	YY**Y**XYY	8.56E-03	YYXXYY	0	YYXXYY	0
5.	ZZYYXY	ZZ**ZZ**XY	5.03E-03	ZZYYXY	0	ZZYYXY	0
6.	XXZYWY	**Y**XZY**X**Y	8.45E-03	XXZYWY	0	XXZYWY	0
7.	ZYYYZZ	Z**Z**YYZZ	4.87E-03	Z**Z**YYZZ	3.82E-08	ZYYYZZ	0
8.	YYYXXX	**ZZ**YXXX	7.32E-03	**Z**YYXXX	2.95E-08	YYYXXX	0
9.	ZYZYXW	ZYZ**ZX**X	6.54E-03	ZYZYX**X**	1.75E-08	ZYZYXW	0
10.	XYYZWZ	**Y**YYZ**X**Z	7.43E-03	XYYZWZ	0	XYYZWZ	0

From table III the (16-16-1) MLP neural network models 1,4 and 7 are settled with single error in the risk level codes and other models are with in two level errors in the higher side of the risk level patterns. This is inherently due to the lower threshold of the classifier and these results in heavy false alarms of 4.58%. In the(4-4-1) MLP models 7,8 and 9 are settled at single error due to false alarm of 0.624 %. The (2-4-2) MLP Neural network is perfectly identified all the patterns without any error or any additional training cost when compare to (16-16-1) & (4-4-1 MLP Neural network models.

A. Quality Value

The goal of this research is to classify the epileptic risk level with as many perfect classifications and as few false alarms as possible. In Order to compare different classifier we need a measure that reflects the overall quality of the classifier [11]. Their quality is determined by three factors.
Classification rate, Classification delay and False Alarm rate, The quality value Q_V is defined as

$$Q_V = \frac{C}{(R_{fa} + 0.2) * (T_{dly} * P_{dct} + 6 * P_{msd})} \qquad (8)$$

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. Table IV shows the Comparison of the fuzzy and neural network optimization techniques. It is observed from table IV, that (2-4-2) MLP neural network is performing well with the highest performance index and quality values.

Table IV Results of Classifiers taken as Average of all ten Patients

Para Meters	**Fuzzy Techniques before optimization**	**MLP Neural Network (16-16-1)**	**MLP Neural Network (4-4-1)**	**MLP Neural Network (2-4-2)**
Risk level classification rate (%)	50	96.42	99.37	100
Weighted delay (s)	4	1.92	1.98	2
False-alarm rate/set	0.2	0.0458	0.00624	0
Performance Index %	40	96.29%,	99.34%	100
Quality value	**6.25**	**22.05**	**24.43**	**25**

The neural network is a slow response method with inheriting weighted delay of 2 seconds. The other two MLP neural networks are exhibiting quick responses with weighted delay of 1.92 seconds and 1.98 seconds respectively. These MLPs are placed with low performance indices and quality values.

V. 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 fuzzy 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. MLP neural network optimization technique is used to optimize the risk level by incorporating the above goals. 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. A comparison of Elman and Radial Basis Network will be taken for further studies.

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