Performance Analysis of Soft Decision Trees Models for Fuzzy Based Classification of Epilepsy Risk Levels from EEG Signals

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Abstract— **The purpose of this research is to investigate the feasibility of Game theory based Max-Min optimization of fuzzy outputs for the classification of epilepsy risk levels from EEG (Electroencephalogram) signals. The fuzzy pre classifier is used to classify the risk levels of epilepsy based on extracted parameters like energy, variance, peaks, sharp and spike waves, duration, events and covariance from the EEG signals of the patient. Max-Min SDT (Soft Decision Tree) as post classifier with four methods is applied on the classified data to identify the optimized risk level (singleton) that characterizes the patient's epilepsy risk level. The efficacy of the above methods is compared based on the bench mark parameters such as Performance Index (PI) and Quality Value (QV). A group of ten patients with known epilepsy findings are used for this study. High PI such as 94.56 % was obtained at QV's of 22.42 in the SDT optimization when compared to the value of 40% and 6.25 through fuzzy classifier respectively. We identified that the SDT provides a better performing tool for optimizing the epilepsy risk levels**

Index Terms— EEG Signals, Epilepsy, Fuzzy Logic, Max-Min Soft Decision Trees, Risk Levels

I. Introduction

Making decision under certainty is a perennial part of human predicament [14]. A computer based intelligence agents are empowered with the ability to make decision in a style that reflects human preferences and decision making style. This task requires us to be able to formulate decision functions that can be considered as intelligent they can incorporate our decision attitude [23]. It is clear that the development and understanding of structures which can be used to model intelligent decision making under uncertainty is an important goal [15]. In this research, we review the potential of fuzzy modeling technology as a tool for constructing customized decision making function for medical diagnosis, such as classification of epilepsy risk levels [9]. These functions can be used to evaluate alternative courses of action in a way that reflects as much as possible the preferences of responsible decision maker [24]. Since, the fuzzy technologies have facility for acting as abridge between natural language expression and formal mathematical representation the fuzzy modeling approach can be very useful for incorporating the types of concepts required of an intelligent decision valuation function [19]. A decision making process can fall into one of the three categories:

1. Decision making under certainty in which the data are known deterministically.
2. Decision making under risk in which the data can be described by probability.
3. Decision making under uncertainty in which the data cannot be assigned weights that represent their degree of relevance in the decision process. In effect, under certainty the data are well defined, and under uncertainty the data are ambiguous. Decision making under risk thus represents, middle of the road case [23]. Decision making under uncertainty a under risk involves alternative actions whose payoff depend on the random states of nature.

A. *Background*

Electroencephalographic (EEG) signals provide information about cerebral activity with an excellent time resolution (in the order of 1ms). Quantitative analysis of EEG signals is generally performed using signal processing methods which may substantially complement the visual inspection of time series. For the past decades, numerous works have been dedicated to the development of SP approaches aimed at evaluating the degree of association. Indeed, the statistical relationship between signals acquired from different brain structures or regions may be used to characterized the functional coupling between recorded sites during normal (cognitive, for instance) or pathological (epileptic, for instance) process [1].

These methods may be divided into two categories depending on whether or not the nonlinear nature of the relationship is taken into account. Linear methods were developed first. Many estimators based on linear cross-correlation or coherence function were purposed and used to study functional couplings between brain regions during mental tasks (Chapman et al) or during epileptic

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process like seizures [2]. Brazier studied the propagation of epileptic activities from intra cerebral recordings [12]. They were followed by Gotman who studied inter hemispheric relations in partial seizures and by Duckrow et al. Franaszczuk who analyzed possible synchronization mechanism occurring at the seizure onset [3].

B. *Motivation*

The Expert and decision support systems are common in the areas where the alternative are selected based on combined support of a number of factors, none of which could determine the alternative by itself. An example of such an area is medicine, where diagnosis or management is almost never decided based on individual criterion [11]. A weighted combination of many criteria is used instead, each criterion may support various alternatives, and the alternative with the strongest support is selected as the decision.

This is a typical problem of multi criteria decision making (MCDM), various approaches to which have been discussed by Gleb Beliakov and Jim Warren (2001). One important class of methods in MCDM is based on constructing a utility or value function u(x), which represents the overall strength of support in favor of the alternative x. this approach, is known as multi attribute utility theory (MAUT) [18].

Several decision making problem meet the necessity of incorporating weights (importance's, frequencies) into quantitative fusion procedure supporting final decision. This is e.g., the case of fuzzy rule-based systems, where a direct application of an exact form of some fuzzy rule is affected by the accessible information about the state of the corresponding antecedent (whose membership value can be understood as its weight). Weights in aggregation (fusion) of several single inputs into one global output arise either from qualitative or quantitative sources [24]. Qualitative aspects may be viewed as importance's of single criteria to be aggregated, e.g., by jury decision making or in rule-based fuzzy control. As an example of this type of weighted aggregation, recall the MAX –operator applied to an input vector $x=(x1,\ldots, xn) \varepsilon [0,1]n$ under importance's

$u=(u1,\ldots, un) \varepsilon [0,1]n$,

$\max_i u_i=1$:

$MAX\ u(x)= \max_i T(u_i,x_i)$

Where $T:[0,1]^2 \rightarrow [0,1]$ is triangular norm.

In FST the aggregation operators take a large variety of forms, e.g., min, max, Yager, Doubios & Prade, Schweizer & Sklar, Hamacher, Frank, Dombi families, averaging operators, ordered weight aggregation (OWA), compensatory operators, operators based on Chouquet and Sugeno integrals, etc. The choice of aggregation operators in FST is not simple. Initially, only min and max operators were used to model fuzzy set intersection and union, primarily because of their strong algebraic properties: these are the only operators that preserve mutual distributives. With the development of the theory other operators have emerged. They provided compensatory properties and better fit to empirical data and, therefore, seemed to model human decision making better[19]-[25]. Nowadays, there are some 90 different families of aggregation operators used in various applications.

C. *Clinical Guidelines in Medical Decision Support System*

The Almost any medical computer application can be classified as a medical decision support system- a computer program designed to help health professionals making clinical decision. In this paper we are considering only those applications that provide clinicians with some form of advice based on symptoms and signs from the electronic patient record. This, of course, does not exclude other forms of advice, such as consultation by the clinician of general information about diseases, treatments, protocols, guidelines, etc. But our primary goal is to develop mechanisms of customizing the advice to the specific problems of a given patient.

This problem has two faces: 1) generation of the advice and 2) its delivery. We have discussed the problem of the delivery of the advice, including fuzzy advice [3], [6]. We limit the scope of this paper to a specific niche of generating advice on treatment and patient management options, based on clinical practice guidelines. Clinical practice guidelines are standardized specifications for care developed by a formal process that incorporates the best scientific evidence of effectiveness with opinions of experts in the field. In general, they have been developed in an effort to reduce escalating health care costs without sacrificing quality and have been shown to improve health care outcomes. To be effective, guidelines need to be integrated into the physician's decision making process in daily practice. It has been recognized that the guideline statements should be linked to the actual patient data, and therefore be integrated with EPR. The most predictable impact is achieved when the guideline is made accessible through computer-based, patient specific reminders that are integrated into the clinician's work flow. That is, ideally one provides guidance just in time in a clinical workstation environment- for example, as with a drug interaction alert at the time a doctor writes a prescription [23].

Most current guidelines are not represented in the form of algorithms. Instead, they are implemented in the form of text narratives, describing possible medical condition and signs with the appropriate recommendations [8]. This fact creates a significant obstacle for computerizing clinical guidelines, their electronic exchange and assessment. Despite recent progress in developing formal syntax for guideline representation, in the computerized form the guidelines are mostly translations of text-based narratives. It is the task of knowledge engineers to extract knowledge from health professionals and to represent guidelines in more suitable form such as the collection of If…then…rules. It turns out, however, that even if formulated as if…then… rules, clinical guidelines are still not suitable for computer implementation [7]. There are different sources of uncertainty present, among which are: lack of information, non specificity, probabilistic nature of data and outcomes, vagueness of recommendations, strife and fuzziness in determination and interpretation of clinical signs [24].

II. METHODOLOGY

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 the 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 [13]. With the help of neurologist, we had selected artifact free EEG records with distinct features.

A. *Fuzzy System as a Pre Classifier*

"Fig. 1", enumerates the overall epilepsy risk level (Fuzzy-Max-Min) classifier system. The motto of this research is to classify the epilepsy risk level of a patient from EEG signal parameters. This is accomplished as:

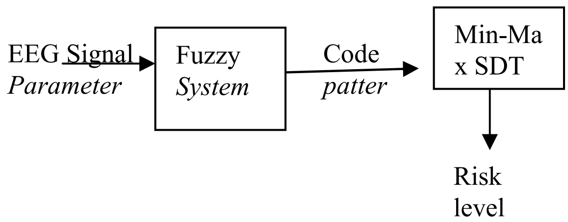

Figure 1: Fuzzy and Max-Min Soft Decision Tree Classification System

a) Fuzzy classification for epilepsy risk level at each channel from EEG signals and its parameters.

b) Each channel results from fuzzy classifier are optimized using Min-Max, method, since they are at different risk levels and highly nonlinear.

c) Performance of fuzzy classification before and after the Min-Max optimization methods is analyzed.

Seven parameters such as Energy, positive and Negative peaks, spike and sharp waves, events, variance, average duration and covariance of duration are calculated for each epoch of EEG signals.

The following seven parameters are extracted from EEG signals which are

1. The energy in each two-second epoch is given by [5]

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

Where x_i is signal sample value and n is number of samples. The scaled 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^2), and is given by

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

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

6 .The average duration is given by

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

Where ti 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

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

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 [24]. 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 56 (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 exhaustive fuzzy rule based system [9].

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. A specific coding method processes the output fuzzy 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. 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 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**
YYYXYY	**ZZYZZZ**	**YYYXYZ**
YYYYYY	**ZZYZYY**	**ZYZZYZ**
ZYYYZZ	**YYYXYY**	**ZYYZZZ**
		YYYXXZ
YYYYYY	**YYYXYY**	**YYYYYZ**
YYYYYY	**YYYXYY**	**YYYXYY**
YYYYYY	**YYYYYY**	**YYYYYY**
ZZYZYZ	**ZZYZZZ**	**ZZYZZZ**

Figure 2: Fuzzy Logic Output

The Performance of the Fuzzy method is defined as follows [4]

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

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

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

The performance for Fuzzy classifier is as low as 40%. It is essential to optimize the out put of the fuzzy systems. Max-Min Soft Decision Tree (SDT) optimization technique (post classifier) [15] is utilized to optimize risk level. A pertinent explanation for the Max-Min optimization is given below.

III MAX –MIN SOFT DECISION TREE (SDT) OPTIMIZATION TECHNIQUE FOR CLASSIFICATION OF EPILEPSY RISK LEVEL

The essence of decision making under uncertainty can be most effectively described using matrix shown below. In this matrix, the Ai corresponds to a collection of actions available to a decision maker, one of which must be chosen. The Sj correspond to the possible values/states associated with a variable U, usually called the state of nature. One and only one of these values can be taken by U. Cij, is the payoff the decision maker receives if he selects alternative Ai and U has the value Sj. The uncertainty associated with this problem is a result of the fact that the value of U is not known before the choice of the decision alternative must be made. The difference between making a decision under risk and under uncertainty is that in the case of uncertainty, the probability distribution associated with the states Sj ; j=1,2,3…n, is either unknown or cannot be determined. This lack of information has led to the development of the following criteria for analyzing the decision problem [10]. Laplace, Mini max, Savage and Hurwitz [20], [22]. These criteria differ in the degree of conservatism the decision maker exhibits in the face of uncertainty.

The Laplace criterion is based on the principle of insufficient reason. Because the probability distributions of the states of nature P {Sj} are not known, there is no reason to believe that they are different [14]. The alternatives are thus evaluated using optimistic assumption that all states are equal likely to occur i.e. P {S1} = P {S2}= P{S3}=… P{Sn}=1/n.

Given that payoff V(ai,sj) represents gain, the best alternative is the one that yields,

Max (ai){(1/n) ∑nj=1 V(ai,sj)}.If V(ai,sj)

Represents loss then minimization replaces maximization. The maxi min (mini max) criterion is based on the conservative attitude of making the best out of the worst possible conditions. If V(ai,sj) is loss then we select the action that corresponds to the mini max criterion. Min (ai){max(sj) ∑nj=1 V(ai,sj)}. As indicated in the reference [23], the procedure used to select the optimal alternative function. We considered the problem of decision making under uncertainty and in particular the formulation of decision (valuation) functions useful for selecting between different alternative courses of action. Since we were interested in the customized construction of these valuations functions, for use in intelligent systems, we introduced the idea of decision attitude as one potential tool for capturing the individual decision style and preferences of the decision maker being modeled.

Apart from several advantages there are some pertinent drawbacks associated with decision trees which are as follows i) Errors may accumulate from level to level in a large tree. ii) Increased in number of terminals when number of classes is large and this lead to increase the search time and memory space requirements [15]. The problem of designing a truly optimal Soft Decision Tree (SDT) is a very difficult one. They also conjecture that no sufficient algorithm exists and thereby supply motivation for finding efficient heuristics for constructing near-optimal decision trees [16].

A. *Algorithm for SDT Optimization*

The various heuristic methods for construction of SDT can roughly be divided into four categories: Bottom-up approaches, Top-Down approaches the hybrid approach and tree Growing – pruning approaches [17]. A decision tree using bottom-up approach was constructed and studied. Using max-min soft decision measures, pair wise distances between a priori defined classes are computed and at each step the two classes with the node decision are merged to form a new group, and this process is repeated until one is left with one group at the root which will be the optimized epilepsy risk level patterns. From a processing point of view, these types of trees are highly recommended.

The generic representation of Max-Min SDT optimization is explained, let W= [Pij] be the co –occurrence matrix with (i,j) elements which represents fuzzy based epilepsy risk level patterns of single epoch. There are 48 (16x3) epochs are available. Now the optimization is a two stage process through Max-Min , which is explained as below,

1. Deduce the 16x3 matrix epilepsy risk level into 16x1 viz row wise optimization through three types of optimization viz, a) Maximum pattern in the particular row, and) Minimum element in that particular row.

2. Deduce the 16x1 matrix into 4 (4x1) matrix one optimum epilepsy risk level through SDT optimization with three levels.

Here also we have two decision methods at node level which are Max-min &Min-max combination. Therefore effectively we have four methods of SDT post classifier such as Min-Min-Max, Max-Max-Min, Min-Max-Min, and Max-Min-Max. SDT (16-4-1) structure is chosen for analysis. The Max-Max-Min is explained as below,

Stage I

1. The minimum method converts the column elements of i,j element into a single row element as BI= min (Pij Pij+1, Pij-1,). Now the row of three elements is converted into single element. This is repeated for all the 16 rows and the matrix is reduced into 16x1 matrixes.

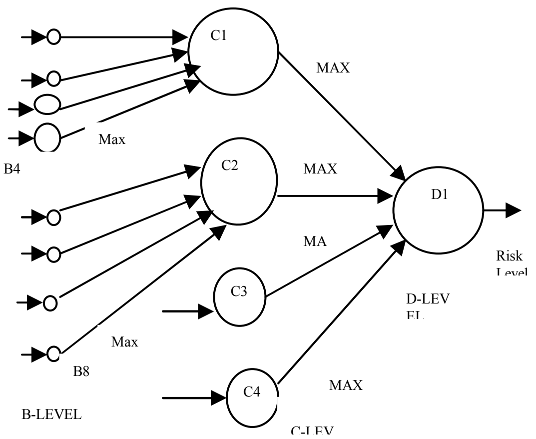

Figure. 3 : Max-Max-Min SDT Optimization Technique.

Stage II: Group (16x1) elements as the leaf nodes of the tree. The next level of tree is named as C with Four decision nodes, which is followed by D level with one soft decision node, which is the root of the tree[16],[17]. Perform the following decisions at the each node of the tree as in the case of Minimum followed by Max-Max method.

Let BI , BI+1 be the ith and i+1 th leaf to be decided at next level CI , as

1. Ci=max (BI,BI+1 BI+2,BI+3), and at next DI level

2. Di=max (CI,CI+1 ,CI+2,CI+3) . The above algorithm is depicted in the figure 3.

In the case of Max-Min –Max procedure the following decisions are taken at the nodes of B, C, and D levels

BI= max (Pij Pij+1, Pij-1,) Let BI , BI+1 be the ith and i+1 th leaf to be decided at next level CI , as

1. Ci=min (BI,BI+1 BI+2,BI+3), and at next DI level

2. Di=max (CI,CI+1 ,CI+2,CI+3)

The obtained singleton results are immensely helpful in devising the therapeutic procedure of the epileptic patients. Results from the four types of optimization methods are discussed in the next section.

IV. RESULTS AND DISCUSSION

Three outputs are obtained for three epochs for every patient in classifying the epileptic risk level by the fuzzy and SDT Optimization approach. To study the relative performance of these two systems, we measure two parameters, the Performance Index and the Quality Value. These parameters are calculated for each set of ten patients and compared.

A. *Performance Index*

A sample of Performance Index for a known epilepsy data set at maximum value is shown in table II. It is evident that the Min-Max-Min Optimization Technique gives a better performance than the fuzzy techniques because of its lower false alarms and missed classifications. Terminology is also important issue when we compare performance of methods. We submit that it is important to differentiate between the two terms of risk level prediction and risk level predictability. The predictability is a necessary but not a sufficient condition for risk level prediction. Risk level predictability has to do with the sensitivity, whereas risk level prediction with both the sensitivity and specificity of a proposed and prospective methods

Table II. Performance Index

Method	Perfect classification	Missed classification	False Alarm	Performance index
Fuzzy Technique	61.25	22	16.75	36.73
Min-Min-Max Optimization Technique	91.4	8.12	0.416	90.4
Max-Max-Min Optimization Technique	92.71	2.082	5.206	92.13
Min-Max-Min Optimization Technique	94.6	4.58	0.833	94.28
Max-Min-Max Optimization Technique	93.34	2.082	4.582	92.86

Hence, it is necessary to present the sensitivity and specificity of epilepsy risk levels classifier with fuzzy and SDT methods. These two precursors are defined as [9],

$$Sensitivity = \frac{PC}{PC + FA} \times 100 \quad (6)$$

$$Specificity = \frac{PC}{PC + MC} \times 100 \quad (7)$$

The sensitivity and specificity parameters for ten epilepsy patients in classification of epilepsy risk levels through fuzzy and SDT methods are shown in figure 4 and 5. It narrates that poor specificity leads to under performance and low sensitivity measures severe false alarms of the system. The average sensitivity and specificity values for ten patients in SDT optimization method is 98.52% and 98.1%. For Fuzzy basic classifier these values are settled at

78.52% and 73.57% respectively. Therefore a compact epilepsy risk level classifier is characterized by its high sensitivity and specificity values.

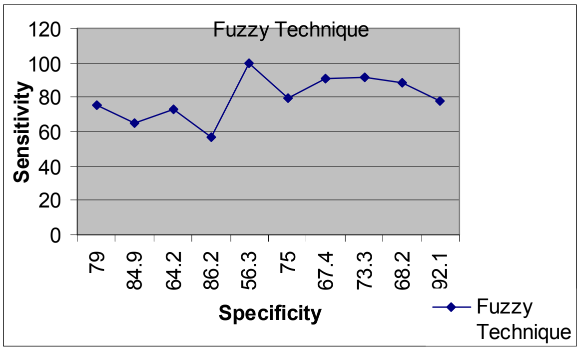

Figure 4: ROC Measures of Fuzzy Technique

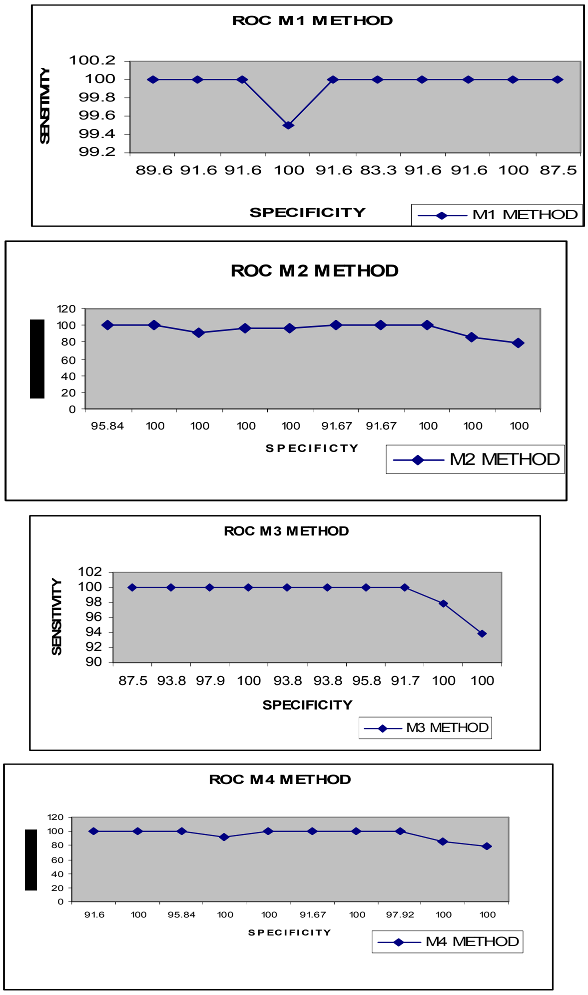

Figure 5: ROC Measures of Four SDT Post classifiers

B. *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 [5]. Their quality is determined by three factors.

(i)Classification rate

(ii) Classification delay

(iii) False Alarm rate

The quality value QV 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

Rfa is the number of false alarm per set

Tdly is the average delay of the on set classification in seconds, Pdct is the percentage of perfect classification and Pmsd is the percentage of perfect risk level missed.A constant C is empirically set to 10 because this scale is the value of QV to an easy reading range. The higher value of QV, the better the classifier among the different classifier, the classifier with the highest QV should be the best.

Table. III Results of Classifiers taken as Average of all ten Patients

Parameters	Fuzzy techniques before optimization	Min-Min-Max Optimization	Max-Max-Min Optimization	Min-Max-Min Optimization	Max-Min-Max Optimization
Risk level classification rate (%)	50	91.4	92.71	94.6	93.34
Weighted delay (s)	4	2.315	1.979	2.166	1.992
False-alarm rate/set	0.2	0.00416	0.05206	0.00833	0.0458
Performance Index %	40	90.4	92.13	94.28	92.86
Quality value	6.25	21.58	20.04	22.15	20.42

Table III shows the Comparison of the fuzzy and SDT optimization techniques. It is observed from table III, that Min-Max-Min SDT method is performing well with the highest performance index and quality values.

V.CONCLUSION

In this paper, we consider generic classification of the epilepsy risk level of epileptic patients from EEG signals. The parameters derived from the EEG signal are complied as data sets. Then the fuzzy methodology is used to the risk level from each epoch at every EEG channel. The target 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. Since, the fuzzy outputs are highly nonlinear in nature with dynamic probability functions. We have chosen game theory based Max-min SDT optimization technique to optimize the risk level by incorporating the above goals. The major bottleneck of this method is that if the adjacent channels have repetitive patterns, then the entire group will be optimized to that particular risk level. This will affect the performance of this SDT Max-Min method. The classification rate of epilepsy risk level of above 90% is possible in our method. The missed classification is almost 2% for a short delay of 2 seconds. From this method we can infer the occurrence of High-risk level frequency and the possible medication to the patients. Further research is in the direction to develop a comprehensive mathematical model to solve this open end problem.

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