Comprehensive Analysis of Hierarchical Aggregation Functions Decision Trees and Minimum Relative Entropy as Post Classifiers in the Classification of Fuzzy Based Epilepsy Risk Levels

R. HariKumar, T.Vijayakumar, M.G.Sreejith

Abstract*— *The objective of this paper is to compare the performance of Hierarchical Soft (max-min) decision trees and Minimum Relative Entropy (MRE) in optimization of fuzzy outputs in 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. Hierarchical Soft decision tree and Minimum Relative Entropy (post classifiers with max-min criteria) four types are applied on the classified data to identify the optimized risk level (singleton) which characterizes the patient's 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).

Index Terms*—: *EEG Signals, Epilepsy Risk Levels, Fuzzy Logic, Hierarchical Decision Trees, Minimum Relative Entropy.

I. INTRODUCTION

Many decisions are based on the determination of available alternatives enduring the relevant criteria. In these types of problems, the measurement of the satisfaction to the individual criteria is available [16]. The constructions of overall decision functions are complicated [8]. First, the construction of decision function requires a specification from the responsible decision maker of the relationship between the criteria for aggregation [12]. Once this specification of relationship and the criteria are obtained, the analyst is then facing with the problem of rendering this information into a form that can be evaluated in terms of the satisfaction to the individual criteria, which leads to the formulation of associated Multi Criteria Aggregation function [15]. This situation puts a premium of knowledge representation structures that allow for both a specification of criteria interrelationships as in the human perception manner, and facilitates this information into formal aggregation functions [18]. Based on the theory of fuzzy measures and the OWA operators, we introduce a hierarchical structure that allows for the construction of decision functions, which meets the above mentioned needs [21].

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Decision trees were popularized by Quinlan with the ID3 program. Perhaps, the most important feature of decision tree is it's capability to break down a complex decision making process into a collection of simpler decisions, thus providing a solution which is easier to interpret [9].

Epileptic seizures are a principal brain dysfunction with important public health implications, as they affect 0.8% of humans [1]. Many of these patients (20%) are resistant to treatment with drugs. The ability to anticipate the onset of seizures in such cases would permit clinical interventions. Traditional signal analyses, such as the count of focal spike density, the frequency coherence or spectral analyses are not reliable predictors [2]. This paper addresses the application of hierarchical structured decision trees and Minimum Relative Entropy (MRE) Techniques towards optimization of fuzzy outputs in the classification of epilepsy risk levels. We also present a comparison of these two classifiers 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, 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. 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.

A. Acquisition of EEG Data

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 [3] [4]. The EEG signal has a maximum frequency of 50Hz and so, each epoch is sampled at a frequency of 200Hz.

Each sample corresponds to the instantaneous amplitude values of the signal, totaling 400 values for an epoch.

B. Fuzzy System as a Pre Classifier

Fig.1. enumerates the overall epilepsy risk level (Fuzzy-HDT/MRE) 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 [5],

1) Fuzzy classification for epilepsy risk level at each channel from EEG signals and its parameters.
2) Fuzzy classifier results from each channel are optimized using four types soft decision trees.
3) Performance of fuzzy classification and the Hierarchical Decision Tree optimization methods are analyzed.

1. The energy in each two-second epoch is given by [6]

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

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.

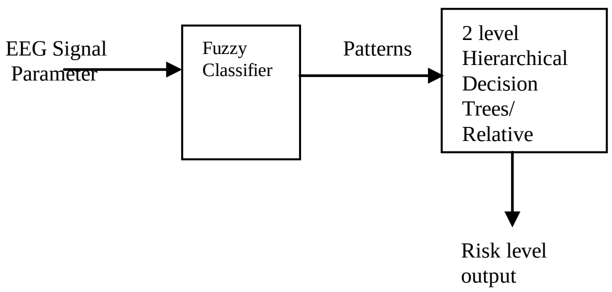

Figure.1. Fuzzy and Hierarchical Decision Tree/MRE Classifier

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

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

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 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

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

C. Fuzzy Membership Functions

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* [7]. 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.*

D. Fuzzy Rule Set

Rules are framed in the format as given below,

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 exhaustive fuzzy rule based system [7].

E. 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. 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 1.

Table.1Representation 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**.** The Performance of the Fuzzy method is defined as follows [6],

$$PI = \frac{PC - MC - FA}{PC} \times 100 \tag{5}$$

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

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

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

Figure.2. Fuzzy Logic Output

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%.

F. Rhythmicity of Fuzzy Techniques

Now we are about to identify the Rhythmicity of Fuzzy techniques which is associated with nonlinearities of the epilepsy risk levels. Let the Rhythmicity is defined as [11]

$$R = C/D \tag{6}$$

Where C= No of categories of patterns; and D=Total number of patterns which is 48 in our case. For an ideal classifier C is to be one and R= 0.0208. Table II shows the Rhythmicity of the fuzzy classifier for each subject.

Table.2 Rhythmicity of Fuzzy Techniques

Patient	No of categories of patterns	Rhythmicity R=C/D
1	9	0.187
2	7	0.1458
3	13	0.271
4	10	0.208
5	7	0.1458
6	9	0.187
7	12	0.25
8	13	0.271
9	14	0.292
10	18	0.375

It is observed from the table 2 that the value of R is highly deviated from its ideal value therefore it is necessary to optimize the fuzzy outputs to endure a singleton risk level. Hierarchical decision trees are used for this purpose. Let the fuzzy outputs as shown in figure 2 is coded with appropriate numerical values. These numerical values are associated with the probability of each coded epilepsy risk level patterns. 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 III. Encoding each output risk level of the fuzzy output gives us a string of six chromosomes, the value of which is calculated as the sum of probabilities of the individual genes. For example, if the output of an epoch is encoded as ZZYXWZ, its value would be 0.333331, [7]. Now the each input patterns are encoded in the numerical form of the range 0-1.

The nonlinearities associated with fuzzy outputs in describing the epilepsy risk levels were identified by cross correlation. Thus the cross correlation function $\mathbf{r_{xy}(m)}$ of the epochs x(n) and y(n) is defined by the equation (7) and assuming that both sequence have been measured from n=0 to n=N-1, in our case n=1to 16,[13]

Table.3 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	

$$r_{xy}(m) = \begin{cases} \dfrac{1}{N}\displaystyle\sum_{n=0}^{N-m-1} x(n+m)y(n), \; for, 0 \le m \le N-1 \\ \dfrac{1}{N}\displaystyle\sum_{n=0}^{N-|M|-1} x(n)y(n+M), \; for, -(N-1) \le m \le 0 \end{cases} \tag{7}$$

The cross correlation r_{xy} (m) plot obtained through the equation (7) is shown in the "Fig.3",which emulates the occurrence of highly non periodic patterns in the fuzzy outputs. Therefore any closed solution will be failed for this purpose of optimization. Hence, it is advisable to prefer non linear techniques instead of linear one, such a one type is HDT. Since, HDT is a common way to solve a wide variety of ill-posed problems which is not necessarily treated as hard constraint one.

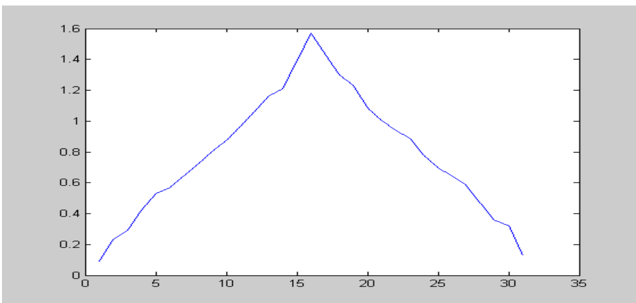

Figure.3. Cross Correlation Function plot for the Adjacent Epochs in fuzzy based Epilepsy Risk Level Outputs

III. HIERARCHICAL DECISION TREES FOR OPTIMIZATION OF FUZZY OUTPUTS

Our objective is to merge the epilepsy risk level representation, with approximate reasoning capabilities, and symbolic decision trees while preserving advantages of both: uncertainty handling and gradual processing of the former with the comprehensibility, popularity, and ease of application of the later. Hierarchical functions are non linear mapping from $(x_1, x_2, x_3, \dots x_n) \in R^n$ to $y \in R$ and this nonlinear mapping is general enough to approximate any non linear function with arbitrary accuracy. In contrast to conventional single stage classifiers where each data sample is tested against all classes, thereby reducing efficiency, in a decision tree a sample is tested against only certain subsets of classes, therefore unnecessary computations are eliminated [8]. The main objectives of HDT are, to classify correctly as much of training samples as possible, generalized beyond the training sample so that unseen samples could be classified with high accuracy (which is also a characteristics gleam of neural networks), easy for updating as more training samples are available, and a simpler structure is also possible.

A. Hierarchical Formulation

Let us review the hierarchical formulation in the R. Yager's perceptive. Again assume we have a set N={N1,…Nn} of directly measurable criteria, that is for each alternative x we can obtained $N_i(x)$, satisfaction of x to N_i. Now we describe the situation which inspires further generalization of our approach. Assume that in choosing an alternative we have two objectives or goals. Goal one, which has an incremental value of β_1= 0.6can be meet with the satisfaction of N1, N2, N3. Goal two which has an incremental value of β_2= 0.4 can be meet with the satisfaction of all N4 to N16 including max-min decisions. In order to model decision imperatives, we shall identify two types of aggregation, weighted average and OWA aggregation [19]. Let V be the q vector with components βi i= 1 to q, lying in the unit interval and summing to one. Then we denote $E_V(y_1,\dots,y_q)$

$$E_V(y_1,...y_q) = \sum_{i=1}^{q} \beta_i y_i = V^T Y \tag{8}$$

Let A be a p dimensional vector with components a_j, j=1to p, that also lies in the unit interval and sum to one. Here we shall denote $F_a(y_1,\dots,y_p)$ to be OWA average of the arguments

$$F_a(y_1,...y_p) = \sum_{j=1}^{p} a_j b_j = A^T B \tag{9}$$

Where b_j is the jth largest of the y_i. Using these two structures we can express the decision function needed to solve the preceding situation [21]. Let D(x) be the overall alternative x letting $N_i(x)=n_i$. We get $D(x) = G(n_1,\dots,n_n)$

$D(x) = E_{V1}(F_{a6}(n_1, n_2, n_3), \max(F_{a5}(n_4, n_5), \min(F_{a4}(n_6, n_7, n_8), \max(F_{a3}(n_9, n_{10}, n_{11}), \min(F_{a2}(n_{12}, n_3), F_{a1}(n_{14}, n_{15}, n_{16}))))))$. This formulation can be viewed as hierarchical structure [8].

In our approach we consider a decision frame work in which we have a collection, N={N1,N2,N3,…,N16}of primary attributes. These first level concepts are decomposed into other concepts or primary attributes. We continue until we end up with all primary attributes.

B. Algorithm for HDT Optimization

The generic representation of HDT optimization is explained, let W= $[P_{ij}]$ be the co–occurrence matrix with (i,j) elements which represents fuzzy based epilepsy risk level patterns of single epoch and 48 (16x3) patterns are available. Now the optimization is a two stage process through HDT, which is explained as below,

1. Deduce the 16x3 matrix epilepsy risk level into 16x1 viz row wise optimization through two types of optimization viz,

a) Hierarchical method of two level, and
b) Maximum pattern in the particular row.

2. Deduce the 16x1 matrix into one optimum epilepsy risk level through HDT optimization with five 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 HDT post classifier.

Stage I

The Hierarchical method converts the three column elements of i,j element into a single row element as

N_{11}= Max (N_{I1}, N_{I2}) & N_I=Min (N_{11},N_{I3}) which is also depicted in the figure.4

And the other method is self explained in nature. 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 matrix.

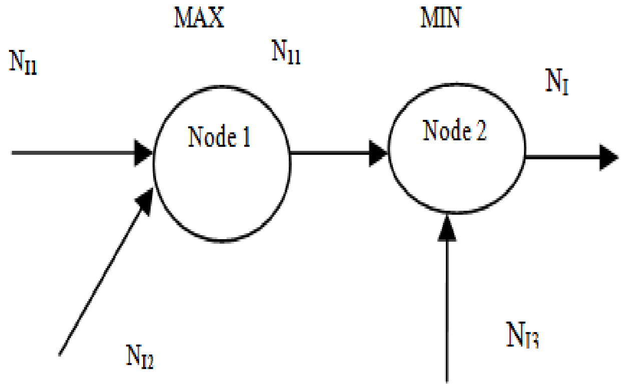

Figure. 4. Hierarchical Method for Row Optimization

Stage II:

Group (16x1) elements as the leaf nodes of the tree N1 to N16. These leafs are aggregated by the rectangular nodes named as A1 to A6. This structure is a mixed averaging hierarchical Decision tree which is depicted in figure 5, we use rectangular box to indicate a weighted average aggregation and a circle used to indicate decision of MAX or MIN. The term inside the symbol indicates the associated vector. The outputs of A nodes are hierarchically combined by the circular B, Soft decision nodes of B1 to B4. The single node V1 (RECTANGULAR) is the root of the tree. In the case of Hierarchical method followed by hierarchical **Max-min method,** let N1,N2 … N16 leaf nodes are available.

The aggregate weights of A nodes are as, For A1, A3, A4, &A6 = $\begin{bmatrix} 0.4 \\ 0.3 \\ 0.3 \end{bmatrix}$ and A2 &A5= $\begin{bmatrix} 0.6 \\ 0.4 \end{bmatrix}$;

And circular nodes B1=Min(A1,A2);B2=Max(A3,B1); B3=Min(A4,B2); B4=Max(A5,B3)

The final V1= $\begin{bmatrix} 0.6 \\ 0.4 \end{bmatrix}$

In the case of **Min –Max** procedure the following decisions are taken at the nodes of Bi for i=1 to 4, when i=odd MAX & i=even Min and also at V1= 0.4(A6) +0.6(B4).

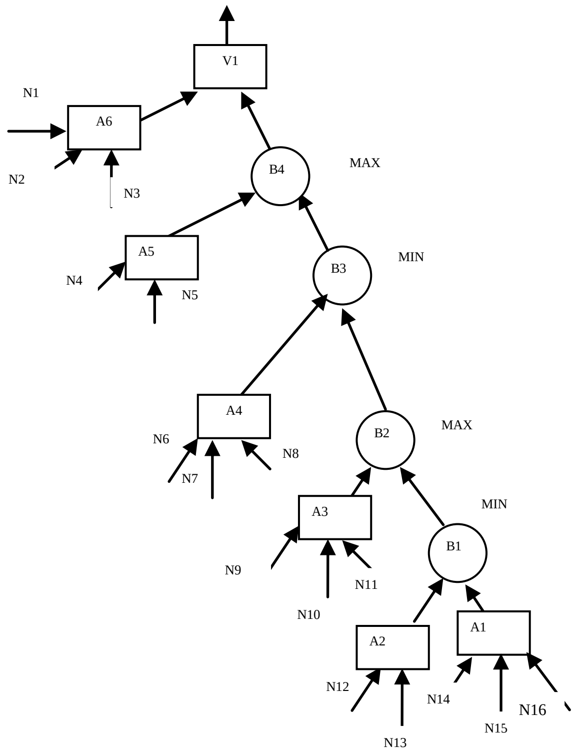

Figure.5. Optimization of Epilepsy Risk Levels through HTD (Max-min) Method

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. MINIMUM RELATIVE ENTROPY (MRE) FOR OPTIMIZATION OF FUZZY OUTPUTS

The EEG signals are inherently complicated due to their non-Gaussian, non-stationary, and often non linear nature. On the top of that, the small amplitude of these signals reinforces their sensitivity to various artifact removal and noise sources [1]. Information theoretic approach to pattern recognition has received considerable interest in recent years. Two concepts have been widely used as recognition criteria, Shannon's entropy and Relative entropy (also known as Kullback-Leibler information distance, directed divergence, cross entropy). The former allows us to measure the information content of a group of patterns and the latter enables us to describe the discrepancy between two groups of patterns [17]. Many entropy based methods have been proposed to maximize Shannon's entropy in the sense that a group of patterns can retain maximum information [12].

By contrast, several relative entropy based methods are also developed to minimize the relative entropy between a groups of patterns and to select an optimum. The following section discusses the issues associated with the optimization of fuzzy output, which in turn represent epilepsy risk levels of a patient using MRE techniques.

A. Algorithm for MRE Optimization

The generic representation of MRE optimization is explained, let p_m and q_n be probability measures for sources M and N, respectively. The relative entropy distance D (N||M) (also known as Kullback-Leibler distance) is defined as [14]

$$D(N \parallel M) = \sum_n q_n(x) \log \frac{q_n(x)}{p_m(x)} \qquad (10)$$

D (N||M) is a nonnegative continuous function and equals to zero iff p_m and q_n coincide. Thus D (N||M) can be naturally viewed as a distance between the measures p_m and q_n. However, D (.||.) is not a metric because it generally is neither symmetric, nor satisfies the triangle inequality. It is not difficult to see that we can have D (N||M) equal to zero while the conditional entropy rate H(N| M) is large and vice versa. Thus, an information distance based on relative entropy can be used as an optimizer for clinical decisions.

Let W= [P_{ij}] 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 three stage process through MRE, which is explained as below,

1. Deduce the 16x3 matrix epilepsy risk level into 16x1 viz row wise optimization through MRE
2. Deduce the 16x1 matrix into 4x1 through column wise optimization.
3. Reduce 4x1 matrix into one optimum epilepsy risk level.

Stage 1

1. 16x3 matrix corner elements are padded with the same elements to avoid log (a_{11}/a_{11}) =0
2. To find out P(i,j) relative entropy of $(i,j)^{th}$ element in the W(i,j) matrix through four neighborhoods.
   $Pi_{,1}(i,j)=P(i-1,j)+P(i+1,j)+P(i,j+1)+P(i,j-1)$,
   where $P(i-1,j)=a_{i-1}\ln(a_{i-1}/a_i)$.
3. Likewise we find $P_{i,2}(i,j+1)$, $P_{i,3}(i,j-1)$, and find min ($P_{i,1}(i,j)$, $P_{i,2}(i,j+1)$, $P_{i,3}(i,j-1)$).

Now the row of three elements is converted into single element and replace the value of min (P (i,j)) with original probability values.

This is repeated for all the 16 rows and the matrix is reduced into 16x1 matrix.

Stage 2:

1. Group 16x1 matrix into 4 co occurrence matrix of 4x1.
2. Using adjacent neighborhoods of the (i,1) element, We find relative entropy P(i)=P(i+1)+P(i-1), P(i+1)=P(i)+P(i+2) and P(i-1)=P(i)+P(i-2),
3. Find the min{P(i),P(i+1), P(i-1)}for a member in that particular group.
4. Like wise for other members in that group find minimum MRE. Therefore there will be four minimum points and find the least min in the group. Likewise 4x1 matrices are arrived.

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Stage 3:

Repeat the stage 2 process and reduce 4x1 matrix into single optimum value which represents the optimum epilepsy risk level.

V. RESULTS AND DISCUSSION

To study the relative performance of these Fuzzy techniques and HTD systems (4 Types), 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 average value is shown in table 4. It is evident that the HTD optimization with [MAX & h Max-min] method as well as [MAX & h Min-max] method gives a better performance than the MRE optimization, fuzzy techniques and other two hierarchical techniques because of its lower missed classifications.

Table. 4 Performance Index

Methods	Perfect Classi fication	Missed Classi fication	False Alarm	Perfor mance Index
Fuzzy logic	50	20	10	40
hier &h max-min	95.42	3.33	1.25	95.2
hier & h min-max	95.63	4.16	0.208	95.43
Max &hmax-min	96.84	0.416	2.17	96.77
Max& hmin-max	97.5	0.416	2.08	97.44
MRE Optimization	97.65	1.87	1.45	96.56

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 [6]. Their quality is determined by three factors namely Classification rate, Classification delay, and False Alarm rate. The Quality Value QV is defined by,

$$Q_V = \frac{C}{\left(R_{fa} + 0.2\right) * \left(T_{dly} * P_{dct} + 6 * P_{msd}\right)} \quad (11)$$

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 V shows the Comparison of the fuzzy and HTD optimization techniques. It is observed from table V, that HTD (Max& h max-min) and (Max& h min-max) methods are performing well with the higher performance index and quality values. As such maximum pattern followed by decision trees are empowered with high false alarm rate and also low weighted delay. This indicates the lower threshold value of the classifiers. On the other hand the hierarchical patterns followed by HTD methods are suffered by high missed classification and long weighted delays. Higher delay is the mark of high threshold value of the Classifiers. Hence it is compromised to select HTD (Max & hmin-max) method compared to MRE optimization, Fuzzy techniques and other HTD methods.

Table. 5 Results of Classifiers Taken As Average of all Ten Patients

Methods	Weighted delay (s)	False-alarm rate/set	Perfor mance Index %	Quality value
Fuzzy logic	4	0.2	40	6.25
hier&hmax-min	2.108	1.25	95.2	22.32
hier&hmin-max	2.1662	0.208	95.43	20.95
Max&hmax-mi n	1.962	2.71	96.77	22.44
Max&hmin-ma x	1.975	2.08	97.44	22.93
MRE Optimization	2.0452	0.0145	96.56	23.02

VI. CONCLUSION

In this paper, we consider generic classification of the epilepsy risk level of epileptic patients from EEG signals and investigated the performance of MRE in optimizing 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 logic is used to the risk level from each epoch at every EEG channel. MRE and HTD optimization techniques were chosen to optimize the risk level by incorporating the low false alarm and near nil missed classifications. HTD (max & hmin-max) has better performance index whereas HTD performs better than MRE optimization techniques and Fuzzy Techniques with high Quality value and with moderate time delay. 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. The future research is in the direction of a comparison of SVM between heuristic MLP and Elman neural network optimization models.

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