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Classification and Analysis of EEG Brain Signals for Finding Epilepsy Risk LevelsUsing SVM

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Abstract: Electroencephalogram (EEG)remainsthe brain signal processing system that tolerates gaining the appreciative of the multipartinternal mechanisms of the brain and irregular brain waves have exposed to be associatedthroughexact brain syndromes. The study of brain waves shows an essentialpart in analysis of dissimilar brain syndromes.Currently there are many people in the world who are suffering from severe brain related illnesses. The physical state or condition of the patient can be assessed by analysing his EEG data. Doctors thus feel a need to check on the EEG data of a patient from time to time. This is where the proposed system comes into play. It provides a means for doctors to analyse the patient's EEG data without direct interaction. Objective of this research work is to associate the classification of epileptic risk level from (Electroencephalogram) EEG signal thenperformance analysis of Support Vector Machine (SVM) and Minimum Relative Entropy (MRE) in optimization of fuzzy crops in the classification of epileptic risk levels from EEG warning signal. The fuzzy preclassifier is castoff to classify the risk phases of epilepsy based on extractedlimitssimilarto energy, variance, peaks, sharp, spike waves, duration, events and covariance after the EEG signs of the patient. Support Vector Machine and Minimum Relative Entropy are useful on the categorized data to recognize the enhanced risk level (singleton) which designates the patient's risk level. The effectiveness of the aboveapproaches is related based on the bench mark boundaries such as Performance Index (PI), then Quality Value (QV).

Key words: Electroencephalogram (EEG) · EEG Signals · Epilepsy Risk Levels · Fuzzy Logic · Minimum Relative Entropy · Support Vector Machine

INTRODUCTION

Artificial intelligence is an intense area of modern-day research holding sway over diverse application fields that include finance, robotics and medicine, to name a few [1]. Twenty –five percent of the world's 50 million people with epilepsy have seizures that cannot be controlled by any available treatment [1]. The need for new therapies and success of similar devices to treat cardiac arrhythmias, has spawned an explosion of research into algorithms for use in implantable therapeutic devices for epilepsy [2]. Most of these algorithms focus on either detecting unequivocal EEG onset of seizures or on quantitative methods for predicting seizures in the state space, time, or frequency domains that may be difficult to relate to the Neuro physiology of epilepsy [3]. Exploring various analytical approaches to process data from medical database is meaningful before deciding on the tool that will be most useful, accurate and relevant for practitioners. The electroencephalogram (EEG), the recording of electrical activities of the brain, is a non-invasive, inexpensive tool, used to analyze and diagnose many neurological disorders such as epilepsy, dementia and coma. Epileptic seizures are a principal brain dysfunction with important public health implications, as they affect 0.8% of humans. Many of these patients (20%) are impervious to handling with medications. TheCapability to forestall the beginning of seizures in such cases would authorizationmedicalinvolvements. Outdated signal analyses, such as the amount of focal spike concentration, the frequency coherence or spectral scrutinizes are not reliable predictors [1]. This paper reports the application of SVM and MRE Techniques headed intended for optimization of fuzzy productions in the classification of epilepsy risk levels [4]. We also present a comparison of these two classifiers based on their performance indices and quality values.

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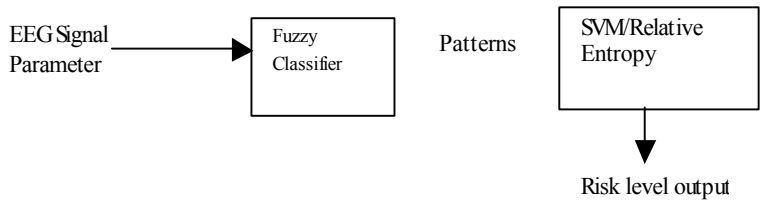

Fig. 1: System design for Fuzzy, SVM and MRE Classifier

Resources and Techniques: Unfortunately, EEG is frequentlypolluted by signals that have non-cerebral origin and theyremainnamed artifacts, which staytriggered by eye movement, eye blink, electrodemovement and muscle activity, movements of the head, sweating, breathing, heartbeat and electrical line noise and so on. The EEG data used in the study were acquired from ten epileptic patients who had been under the estimation and behavior in the Neurology department of Miot Hospital, Chennai, India. A broadsheet 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 sensibly accurate finding of epilepsy is conceivable; however, complicationsascend with artifacts. This delinquentupsurges the number of incorrect detection that commonly plagues all classification systems.With the help of neurologist, we had selected artifact free EEG records with differenttypes. These archives were perused by Umax 6696 scanner with a resolution of 600dpi.

Attainment of EEG Data: The EEG is a measure of voltage as a function of time. The voltage of the EEGregulates its generosity (measured from peak to peak). EEG generosities in the cortexvariety from 500-1500 µV, however, the generosities of the scalp EEG range between 10and 100 µV [5-7]. Meanwhile the EEG archives are over a nonstopperiod of around thirty seconds; they are detached into periods of two second intermissionseparately by skimming into a bitmap image of size 400x100 pixels. A two second epoch is stretchedgenerous to noticeroughlyextensivevariations in measurethenoccurrence of artifacts and similarly short ample to avoid somewhatduplication or termination in the signal [3, 8, 9]. The EEG signal has anextreme frequency of 50Hz then so, apiece epoch is tested at a frequency of 200Hz. Individualsampleequals to the instantgenerosityideals of the signal, gathering 400 values for an epoch.

Fuzzy System as a Pre Classifier: Fig. 1. Counts the complete epilepsy risk level (Fuzzy-SVM-MRE) classifier system. The motto of this research is to classify the epilepsy risk level of a persistent after EEG signal limitations. This is proficientby way of [10];

- Fuzzy classification for epilepsy risk level at separate channel from EEG signals and its parameters.
- Fuzzy classifier results from each channel are optimized using four types soft decision trees.
- Performance of fuzzy classification, SVM and MRE optimization methods are analyzed.
- 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 scaled energy is taken by dividing the energy term by 1000.

- The completeamount of positive and negative peaks exceeding a threshold is found.
- 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.
- The total numbers of spike and sharp waves in an epoch are recorded as events.
- 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.

- The average duration is given by

$$D = \frac{\sum_{i=1}^{p} t_i}{p} \tag{3}$$

where t_i is unique peak to peak intervals and p is the number of such intervals.

- Covariance of Duration. The variation of the average duration is defined by

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

Fuzzy Membership Functions: Energy is associated with the additional six input features to provide six outputs. Each input feature is categorized into five fuzzy semanticphasesviz.very low / low / medium / high and very high [11]. The triangular membership functions are used for the linguistic levels of energy, peaks, variance events, spike, sharp waves, average interval and covariance of interval. The production risk level is categorized into five semanticstagesspecificallynormal / low / medium / high and very high.

Fuzzy Rule Set: Rules are framed in the format UncertaintyIF Energy is short AND Variance is little THEN Output Risk Level is low In this fuzzy classification we have five linguistic stages of energy and five linguistic stages of other six typesnamely variance, peaks, events, spike, sharp waves, average time interval and covariance of time interval. Ideally there may be 5^6(to be exact 15625) guidelines are conceivable but we had measured the fuzzy pre -classifier as a mixture of six two inputs andone output (2×1) system. With energy being a constant one input the other input is selected in sequential manner. This twofold inputs single output (2×1) fuzzy method mechanism through 25 rules. We achieveanoverall rule base of 150 rules created on six sets of 25 rules respectively. This is a type of exhaustive fuzzy rule based system [4, 11].

Estimation of Risk Level in Fuzzy Outputs: The output of a fuzzy logic signifiesanextensive space of risk levels. This is because there are sixteen dissimilarnetworks for input to the scheme at three epochs. This contributes a complete of forty-eight input output couples. Meanwhile

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

Fig. 2: Output using Fuzzy Logic

Table I: Representation of Risk Level Classifications

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

we contract with identified cases of epileptic patients, it is essential to discover the exact level of risk the patient. This fortitudeis correspondinglysupport in the development of automated classifications that can exactly classify the risk level of the epileptic persistent under surveillance. Hereafter an optimization of the yields of the fuzzy scheme is important [12]. This resolve recovers the classification of the patient and can provide the EEG through a vibrantimage. The alphabeticexemplificationof the five classifications of the productions is presented in Table-I.

A trialproduction of the fuzzy system with real patient interpretations is shown in Fig. 2 for eight frequenciesterminatedin three epochs. It can be comprehended that the frequency 1 displays medium risk levels while channel 8 displaysactual high risk levels. Similarly, the risk level classification differsamongcontiguous epochs. The Performance of the Fuzzy technique is defined as follows [13].

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

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

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

The perfect classification signifies when the doctors and fuzzy classifier approves with the epilepsy risk level. Missed classification signifies a true negative of fuzzy classifier in orientation to the doctor and shows High

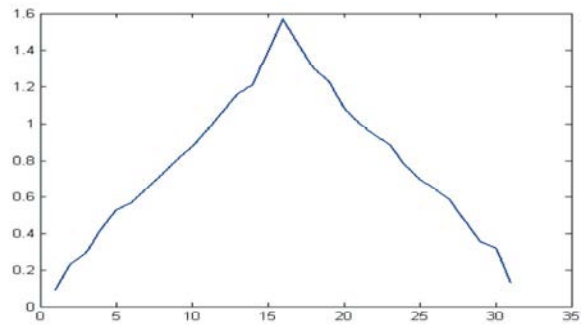

Fig. 3: Cross Correlation Function plot for the Adjacent Epochs in fuzzy based Epilepsy Risk Level Outputs

Table III: Binary Representationof 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

level as Low level. False alarm signifies a false positive of fuzzy classifier in orientation to the doctor and displays Low level as High level. The presentation for Fuzzy classifier is as low as 40%.

Binary Representation of Risk Level Patterns: The five risk levels are determined as Z>Y>X>W>U in binary sequences of interval five bits via weighted positional exemplification as displayed in Table-II. Encrypting each production risk level of the fuzzy productionprovides us a sequence of six chromosomes, the significance of which is considered as the quantity of possibilities of the different genes. For sample, if the production of an epoch is encrypted as ZZYXWZ, its significance would be 0.333331 [11]. Now the each input patterns are encoded in the numerical form of the range 0-1.Now we are about to identify the nonlinearities associated with fuzzy outputs in describing the epilepsy risk levels. Thus the cross correlation function rxy(m) of the epochs x(n) and y(n) is defined by the equation (6) and assuming that both sequence have been measured from n=0 to n=N-1, in our case n=1to 16, [12].

$$r_{xy}(m) = \begin{cases} \frac{1}{N}\sum_{n=0}^{N-m-1} x(n+m)y(n), for, 0 \le m \le N-1 \\ \frac{1}{N}\sum_{n=0}^{N-|M|-1} x(n)y(n+M), for, -(N-1) \le m \le 0 \end{cases} \quad (6)$$

The cross correlation r_{xy} (m) plot obtained through the equation (6) 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 nonlinear techniques instead of linear one, such a one type is MRE. Since, Minimizing relative entropy is a common way to solve a wide variety of ill-posed problems which is not necessarily treated as hard constraint one [14].

Support Vector Machine as Post Classifier: Popular fuzzy techniques new suboptimal clarifications are attained. These elucidationsare improved andaenhancedelucidationis inwardsfor identifying patient's epilepsy risk level. Intended forthe optimization of fuzzyproductions the Support Vector Machine (SVM) technique is recognized [7].

The succeedingresponsibilitiescontinueacceptedto classify the risk levels through SVM which remain,

- Initially a simplest case is examined with hyper plane as result function with the known linear data.
- A nonlinear classification is throughaimed at the encryptionsattainedafter a specific patient by by means of quadratic discrimination [5].
- Formerly the k-means [2] clustering is achieved for enormous data with dissimilargroups of clusters with centroid for individually.
- The centroid attained is recorded by the kernel function for findinganappropriate shape.
- A linear separation is gainedthroughconsuming SVM by kernel and k-means clustering

The nextexplanation constrains phases are charted:

Step 1: The linearization in addition to convergence is thruby Quadratic Optimization. The primal minimization problematic is improvedhooked on its dual optimization problem of exploiting the dual lagrangian L_D with respect to α_i:

$$\text{Max } L_D = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j (X_i \cdot X_j) \quad (7)$$

Subject to

$$\sum_{i=1}^{l} \alpha_i y_i = 0 \quad (8)$$

$$\alpha i \ge 0 \ \forall i=1,\ldots\ldots,l \quad (9)$$

Step 2: The optimal splitting hyper plane is created by resolving the quadratic programming problem clear by (7)-(9). Nowin this solution, individuals points need non-zero Lagrangian multipliers (a_i>0) remaindesignated support vectors.

Step 3: Support vectors lie neighboring to the choice boundary. Accordingly, the optimal hyper plane is one determined by the support vectors in the exercise data.

Step 4: The k-means clustering is complete for the specified set of data. The k-means function will form a collection of clusters allowing to the circumstancerecognized in step-2 and step-3. Expect for a collection of 3 clusters, k-means function resolveindiscriminately choose threecenter points after the given set. Individuallycenter point will obtain the values that are existingaboutthem [6].

Step 5: Now nearby will be six center points three afterseparately epochs and formerly the SVM training procedure is complete by the Kernel techniques. Therefore, merely the kernel function is recycled in the training algorithm and one does not essential to distinguish the clear form of *Ø*. Some of the frequently used kernel functions are:

Polynomial Function: $K(X, Y)=(X^T Y+1)^d$

Radial Basis Function: $k(xi, xj) = \exp\{\frac{-|xi-xj|^2}{(2*\sigma)^2}\}$

Sigmoid Function: $K(X, Y)=\tanh(kX^T Y+\theta)$

Support Vector Mechanism for Optimization of Fuzzy Outputs: An essentialissue for the best of a classification technique for a given problem is the offered a-priori understanding. Through the previous few years support vector machines (SVM) have revealed to be broadlyappropriate and successful specific in cases where a-priori knowledge contains of categorized learning information. If additional knowledge is presented, it is practical to incorporate and model this knowledge within the classification outcomes or to involvefewer training data. Consequently, much lively research is distributing with adjusting the overall SVM methodology to cases where extra a-priori knowledge is obtainable. We have absorbed on the collective case where predictability of data can be exhibited by renovations which leave the class associationuntouched. If these alterations can be modeled by mathematical collections of transformations one can include this knowledge self-sufficiently of the classifier throughout the feature extraction stage by cluster integration, normalization etc. this indications to variant features, on which some classification algorithm can be realistic [15].

The situation is noted that one of leadingexpectations of SVM is that all examples in the training set are Independent and Identically Distributed (I-I-D), however, in numerous practical engineering applications; the gained training data is frequentlypolluted by noise. Further, more or less samples in the training data set remain misplaced on the incorrect side by chance. These identified as outliers. In this case, the regular SVM training algorithm will make decision boundary departstrictlyafter the optimal hyper plane, such that, the SVM is exactthoughtful to noise and exclusively those outliers that are close to decision boundary. This marks the ordinary SVM no longer sparse, i.e., the quantity of support vectors upturns significantly due to outliers [16]. Now in this paper, we present anoveralltechnique that follows the main knowledge of SVM by means of adaptive margin aimed at each data point to communicate the minimization problem, which routines the RBF kernel trick [17]. It is prominent that the grouping functions achieved by decreasing MSE are not complex to outliers in the training set. The purpose that traditional MSE is resistant to outliers is that it is an average algorithm. Aindividual sample in the training set merelysubsidizes little to the ultimateoutcome. The consequence of outliers can be removed by winning average on samples. That's why the average technique is a simple yet operative tool to hold outliers.

Striving by the two deliberationsaround the adaptive margin and average algorithm, we recycled the spaceamong the centers of each class of the training data, the model point to procedure an adaptive margin. A novelsagging variable is presented in the optimal function, which is the creation of a pre designated parameter and the square distance amongapiece data point to the center of the individual class. While we do not straight solve the optimization problem by minimizing MSE here, we do use the center of class representing the averaged information of the noisy training set to the margin. Therefore, the adaptive margin will make the SVM less sensitive to some specific samples, such in place of outliers.

We make use of the RBF kernel functions thensimilarly decision functions for defining the boundary of each class. Meanwhile we remainexamining twenty epilepsy patients through leave one out methods and

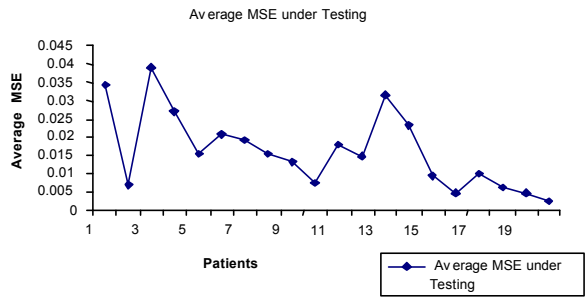

Fig. 4: Graph for Average MSE under the Testing of SVM Prototypes

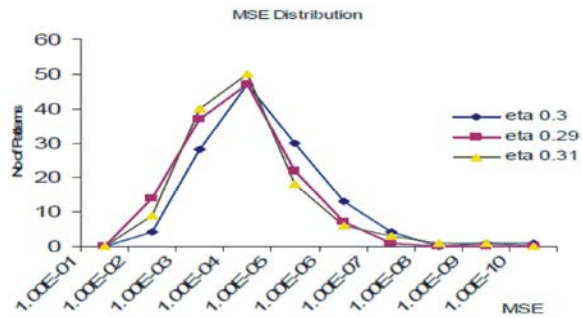

Fig. 5: Graph for selection of Learning Rate

tenfold cross validation. Established on the MSE value then Average MSE values of SVM simulations the classifications of epilepsy risk levels are confirmed. The outliers problem is elucidated through Average MSE technique which is displayed in Fig. 4 and Fig. 5. After the training completed by the outliers the PC of epilepsy risk level is slithered to 95% level and in conclusionentirely the sets of data remain trained the PC is stable at 98% only.

Minimum Relative Entropy (MRE) for Optimization of Fuzzy Outputs: The EEG signals remainintrinsicallydifficult due to their non Gaussian, non stationary and often non- linear nature. Preceding the top of that, the minorgenerosity of these signals strengthens their sensitivity to numerousartifact removal and noise sources [1]. Information theoretic approach to pattern recognition has received considerable interest in recent years [18]. 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. Many entropy based methods have been proposed to maximize Shannon's entropy in the sense that a group of patterns can retain maximum information [7].

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 [18].

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

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= $[P_{ij}]$ remain the co-existence matrix through (i,j) elements which signifies fuzzy centered epilepsy risk level patterns of particular epoch. Around 48 (16x3) epochs are obtainable. Currently the optimization is a three phaseprogression through MRE, which is explained as below,

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

Stage 1:

- 16x3 matrix corner elements are padded with the same elements to avoid log (a_{11}/a_{11}) =0
- 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$P(i-1,j)=a_{i-1}\ln(a_{i-1}/a_i)$.

- 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:

- Group 16x1 matrix into 4 co occurrence matrix of 4x1.
- 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),
- Find the min{P(i),P(i+1), P(i-1)}for a member in that particular group.
- 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 matrixes are arrived.

Stage 3: Repeat the stage 2 process and reduce 4x1 matrixes into single optimum value which represents the optimum epilepsy risk level.

RESULTS AND DISCUSSIONS

Towardtrain the relative performance of these Fuzzy techniques SVM and MRE systems, we measure dual parameters, the Performance Index and then the Quality Value. These parameters remainpremeditated for individual set of ten patients then compared.

Performance Index: A sample of Performance Index for a known epilepsy data set at average value is shown in Table IV. It is evident that the SVM optimization method gives a better performance than the MRE optimization and fuzzy techniquesbecause of its lower missed classifications.Terminology is alsoimportant issue when we compare performance of methods.We submit that it is important to differentiate between the twoterms of risk level prediction and risk level predictability. Thepredictability is a necessary but not a sufficient condition forrisk level prediction. Risk level predictability has to do withthe sensitivity, whereas risk level prediction with both thesensitivity and specificity of a proposed and prospectivemethods.

Hence, it is necessary to present the sensitivity andspecificity of epilepsy risk levels classifier with fuzzy and SVM, MRE methods. These two precursors are defined as

$$Sensitivit\ y = \frac{PC}{PC + FA} \times 100 \quad (11)$$

$$Specifcity = \frac{PC}{PC + MC} \times 100 \quad (12)$$

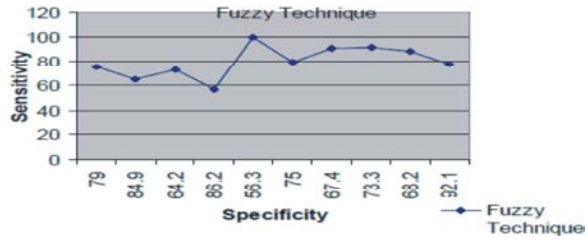

Fig. 6: Graph for Fuzzy Techniques Measures

Table IV: Performance Index for Fuzzy, Svm and MRE

Methods	Perfect Classification	Missed Classification	False Alarm	Performance Index
Fuzzy logic	50	20	10	40
SVM Optimization	97.39	1.458	1.385	97.07
MRE Optimization	97.65	1.87	1.45	96.56

Table V: Estimation of Mse in Various Elman Network Architecture

Architecture	Mean Square Error (MSE)Index		Confidence score C_i=exp(-λe_i^2)
	Training	Testing	
9-9-9	0	3.874E-02	96.2
27-4-1	0	4.21E-03	99.65

The sensitivity and specificity parameters for ten epilepsypatients in classification of epilepsy risk levels through fuzzyand SVM, MRE methods are shown in Figure 4 and 6. It narrates thatpoor specificity leads to under performance and lowsensitivity measures severe false alarms of the system. Theaverage sensitivity and specificity values for ten patients inSVM optimization method is 97.07% and 97.0%. For Fuzzybasic classifier these values are settled at40.0% and 60.2% respectively. Therefore a compactepilepsy risk level classifier is characterized by its highsensitivity and specificity values.

The average confidence score for all Elman Network architecture is tabulated in the Table. 5. Table 5 shows the selection of Elman network architecture based on testing MSE. It is observed from table 4 the architecture 16-16-16 depicts the lowest number of training epochs and lesser MSE in testing. Once the optimal network architecture has been determine, the performance of the network models can be evaluated.In the Elman 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). Therefore we had selected 27-4-1 Elman network [16] architecture which provides more accuracy in the classification which is depicted in Fig. 7.

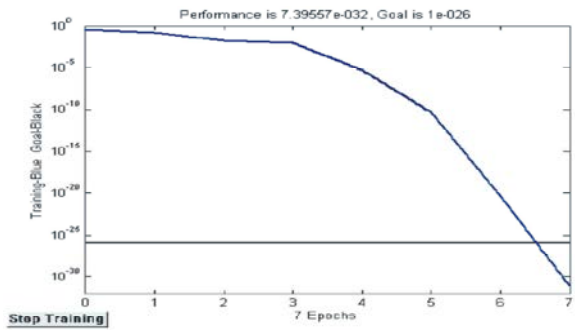

Fig. 7: Training of Elman neural networks

Table VI: Effects of Fuzzy, Svm, Mre Classifiers Reserved as Average of Entire Ten Patients

Methods	Weighted delay (s)	False-alarm rate/set	Performance Index %	Quality value
Fuzzy logic	4	0.2	40	6.25
SVM Optimization	2.031	1.389	97.07	22.93
MRE Optimization	2.0452	0.0145	96.56	23.02

Quality Value: The objective of this research is to classify the epileptic risk level with as numerous perfect classifications and as insufficient false alarms as promising. Nowto associatedissimilar classifier we need a quantity that replicates the comprehensive quality of the classifier [19]. Their quality is strong-minded by three aspectsviz.Classification rate / Classification delay / False Alarm rate.

The Quality Value QV is distinct by,

$$Q_V = \frac{C}{\left(R_{fa} + 0.2\right) * \left(T_{dly} * P_{dct} + 6 * P_{msd}\right)} \quad (13)$$

where, C defines scaling constant, R_{fa} used for number of false alarm for each set, T_{dly} is defined as average delay of the on set classification in seconds, P_{dct} used for the percentage of perfect classification andthen P_{msd} is the percentage of perfect risk level unused. A constant C is empirically set to 10 because this scale is the value of Q_V to an informalinterpretationchoice. The sophisticated 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 displays the Association of the fuzzy and SVM optimizationmethods.This one is perceived from tableV thatSVM methodaccomplishes well through the difficult performance index whereas MRE optimization has better quality value. As such maximum pattern followed by SVM are empowered with high false alarm rate and also low weighted delay. This indicates the lower threshold value of the SVM. On the other hand the hierarchical patterns followed by MRE methods are suffered by high missed classification and long weighted delays [5]. Higher delay is the mark of high threshold value of the Classifiers. Hence it is compromised to select SVM method compared to MRE optimization and Fuzzy techniques.

CONCLUSION

In this paper, we deliberatethe performance of SVM and MRE in enhancing the epilepsy risk level of epileptic patients after EEG signals. The parameters derived from the EEG signal remainaccumulatedas data sets. Then the fuzzy logic is used to the risk level from each epoch at every EEG channel. MRE and SVM optimization techniques were preferred to optimize the risk level by integrating the low-false alarm and near nil unused classifications. SVM ensuresimproved performance index and a lower weighted delayhowever MREhas a high quality valuecompared to SVM optimization and Fuzzy Techniques.

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