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An Enhanced Automated Epileptic Seizure Detection Using ANFIS, FFA and EPSO Algorithms

Sumant Kumar Mohapatra[1], Srikanta Patnaik[2]
[1]Department of Computer Science and Engineering, Institute of Technical Education and Research
Siksha 'O' Anusandhan (Deemed to be) University, Odisha, India
sumsusmeera@gmail.com
[2]Department of Computer Science and Engineering, Institute of Technical Education and Research
Siksha 'O' Anusandhan (Deemed to be) University, Odisha, India
srikantapatnaik@soa.ac.in

Abstract— Objectives: Electroencephalogram (EEG) signal gives a viable perception about the neurological action of the human brain that aids the detection of epilepsy. The objective of this study is to build an accurate automated hybrid model for epileptic seizure detection. Methods: This work develops a computer-aided diagnosis (CAD) machine learning model which can spontaneously classify pre-ictal and ictal EEG signals. In the proposed method two most effective nature inspired algorithms, Firefly algorithm (FFA) and Efficient Particle Swarm Optimization (EPSO) are used to determine the optimum parameters of Adaptive Neuro Fuzzy Inference System (ANFIS) network. Results: Compared to the FFA and EPSO algorithm separately, the composite (ANFIS+FFA+EPSO) optimization algorithm outperforms in all respects. The proposed technique achieved accuracy, specificity, and sensitivity of 99.87%, 98.71% and 100% respectively. Conclusion: The ANFIS-FFA-EPSO method is able to enhance the seizure detection outcomes for demand forecast in hospital.

Keywords- Epileptic Seizure, EEG signal , FFA,EPSO,ANFIS

I. INTRODUCTION

Automatic changes of body condition, losses of concentration are the general manifestations seen amid the event of seizures [1]. The detailed information of World Health Organization (WHO), it is computed that consistently 2.4 million people are determined to have epilepsy [2]. Seizures are made because of the sporadic electrical signal streams over a cluster of neurons [3, 4], which can influence any person at any age [5]. The Signal can characterize with frequency and amplitude [6]. The determination and classification of such abnormalities is a time-consuming process even for an export practitioner also [7]. Distinct observation of epilepsy can be helpful to control the disorder and detection of seizures from EEG signals [8]. For an exact, quick, and target oriented result CAD determination framework is required. Numerous scientists have proposed distinctive ways to deal with consequently identify epileptic seizure utilizing EEG signals. As per the reviews of the authors, see Acharya et al. [9] and Faust et al. [10] applied different effective approaches. Entropy based automated EEG signals are represented in Acharya et al. [11]. Higher Order Spectra (HOS) is applied to observe and analyze the statistical parameters that are significantly appropriate for classification in Chua et al. [12] Chua et al. [13]. Effective Recurrent Quantification Analysis (RQA) method is used with different parameters to operate Support Vector Machine (SVM) that gives an Accuracy of 95.6% Acharya et al. [14]. Higher Order Cumulant features (HOC) are used with SVM classifier provides an Accuracy of 98.5% in Acharya et al. [15]. The work proposes the utilization of a novel strategy, as it is the intrinsic time-scale disintegration (ITD), to calculate the features highlights for the Accuracy of 95.67% in Martis et al. [16]. Embedding and Spectral entropy, Lyapunov exponents are used to a study and the complexities of the system to detect epilepsy in EEG signals. Kannathal et al. [17]; Acharya et al. [18], Guler & Ubeyli [19]. Other important contributions of epileptic seizure detection is summarized in Table 1.

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MAIN CONTRIBUTIONS:

The contributions of this work are the following:

- Fuzzy rule-based systems are designed using ANFIS, FFA and EPSO optimization algorithms.
- Benchmark medical data sets are used to evaluate the effectiveness of the system.
- The method is examined under three experimental. conditions as ANFIS-FFA, ANFIS-EPSO and ANFIS-FFA-EPSO.

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- Comparison among 20 well-known machine learning methods.
- Computation of three well-known statistical parameters are proposed.
- The experiments are validated through ROC-AUC and confusion matrix.

TABLE 1 A SUMMARIZED VERSION OF OTHER CONTRIBUTIONS IN EPILEPTIC SEIZURE DETECTION WORKS

Ref.	Methods	Ref	Methods
[20]	Spike Neural Network (SNN)	[30]	KNN+ Genetic programming
[21]	Levenberg Marquardt backpropagation NN ,Wavelet chaos methodology	[31]	Fuzzy sugeno , HOS Features
[22]	PCA,Enhanced Cosine RBF neural network, Wavelet chaos	[32]	Fuzzy sugeno, Entropy
[23]	Multi-spiking NN	[33]	Fuzzy sugeno, WPD
[24]	GMM	[34]	DWT,SVM
[25]	GMM	[35]	EMD, HT
[26]	GMM	[36]	Random forest , EMD
[27]	SVM+PSD Estimation	[37]	TQWT ,SVM
[28]	SVM+DWT	[38]	LS-SVM, ATFF,WTFD
[29]	SVMRQA	[39]	Ten-fold cross validation, 13-layer DCNN

II. MATERIAL AND METHODS

Five segmented EEG data are collected from Bonn University, Germany database (http://epilepsy.uni-freiburg.de/database) [40]. The data were selected from multichannel EEG signal recorder with a continuous observation used to remove the artefacts. Out of the five data sets three sets of data (Set B, Set D, Set E) normal, pre-ictal and seizure respectively are collected from a group of five patients. Each data set contained 100 EEG signals with 23.6 seconds. The Normal EEG signal from Bonn university dataset is shown in Figure.1. The respective power spectral density (PSD) is shown in Figure. 2. The pre-ictal EEg signal and its PSD form is shown in Figure 3 and Figure. 4 respectively. The ictal EEG signal and its PSD represented in Figure. 5 and Figure. 6 respectively.

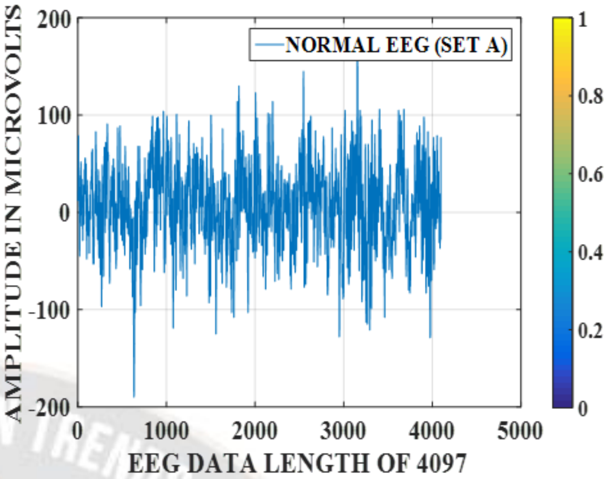

Figure1: Plot of normal EEG signal from set A

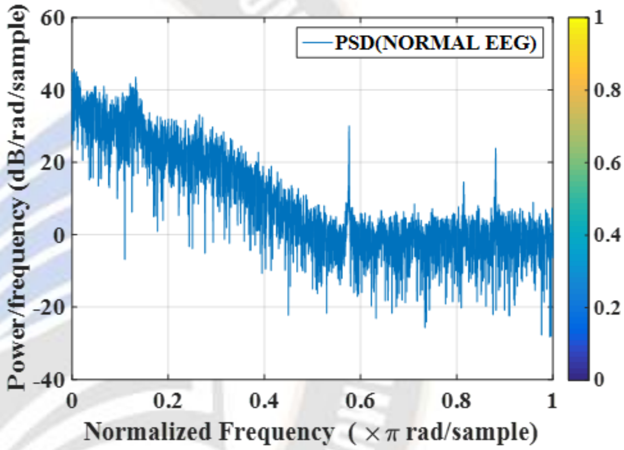

Figure.2: Power spectral density of normal EEG signal.

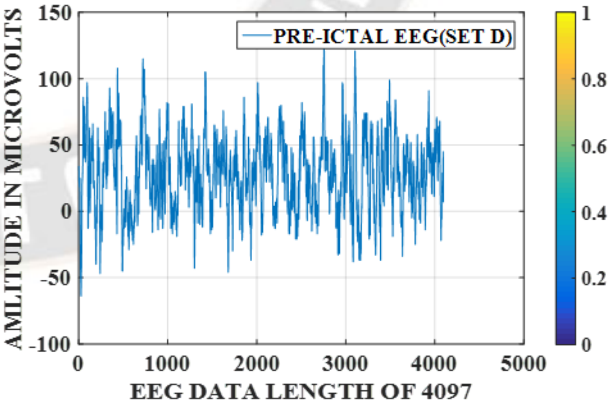

Figure.3: Plot of Pre-ictal EEG signal from set D

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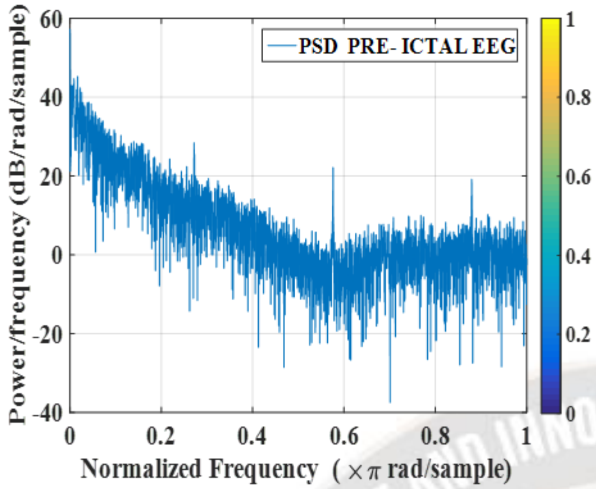

Figure.4: Power spectral density of Pre-ictal EEG signal.

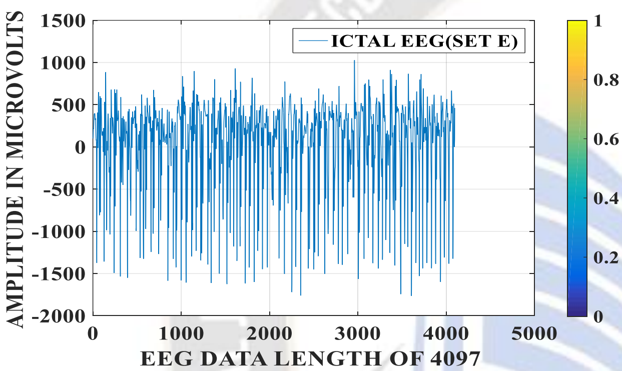

Figure.5: Plot of ictal EEG signal from set E

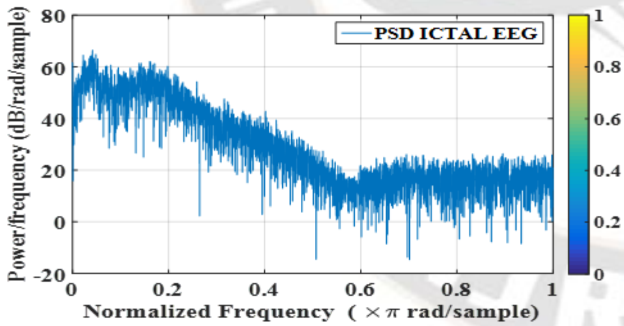

Figure.6: Power spectral density of ictal EEG signal

ADAPTIVE NEURON FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS Network provides a framework between fuzzy system and the learning capacity of neural systems [41,42]. We have used triangular shaped membership function . Nodes of the ANFIS network permits one to build the relationships between input and the output.. The if-then rules are based on their antecedent and consequent parts of the network.

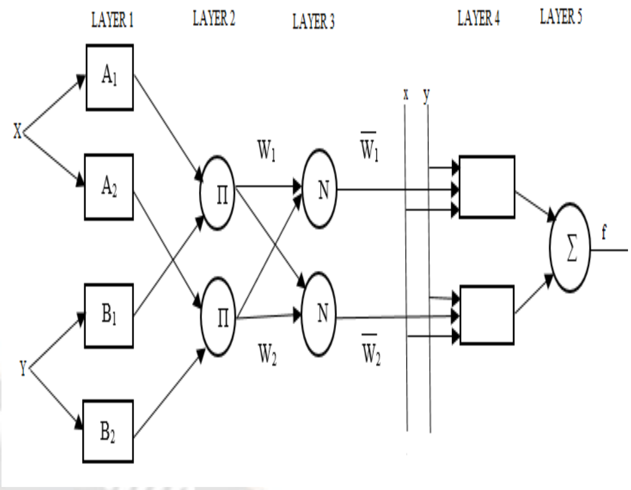

Figure. 7 Model of 2 input one output ANFIS Network

Figure.7 shows the structure of two inputs (x and y) and one output (y) ANFIS network with three hidden layers. An ANFIS model can cleverly separate data and change over it to fuzzy system, yet this a bigger time used in preparing the model is important for precise estimation in [43]. In this study, a Firefly Optimization Algorithm (FFA) and a new Efficient Particle Swarm Optimization (EPSO) are jointly used to train the ANFIS network to achieve better statistical performance.

FIREFLY OPTIMIZATION ALGORITHM (FFA)

Firefly Algorithm (FFA), is a nature inspired algorithm where social behavior of fireflies, based on the flashing characteristics are studied [44, 45].

In FFA algorithm the member of population (i.e Firefly) presents the candidate's solution in a particular search space. Candidate's solution is expressed as in Eqn(1)

$$X_i = (X_{i1,}X_{i2,} \dots \dots .., X_{id}) \qquad (1)$$

Here d is the dimensionality of the problem.

Initialization of the candidate solution is represented as in Eqn(2)

$$x_{ij}^0 = U(0,1).\left(ub_j - lb_j\right) + lb_j \qquad (2)$$

For i=1, 2 …………………n

The variation of light intensity I(r) is related to the encoded objective function as represented in Eqn(3) as:

$$I(r) = I_0 e^{-\gamma r^2} \qquad (3)$$

Where I_0 is the original light intensity and γ is the light absorption co-efficient. I varies exponentially with the square of the distance r i.e $(I \propto r^2)$.

The intensity of light I(r) of firefly at a particular position r can be represented according to Eqn(4)

$$I(r) = \frac{I_s}{r^2} \qquad (4)$$

Where I_s is the intensity of source.

The encoded objective function of ß is represented in Eqn(5)

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$$ß(r) = ß_0 e^{-\gamma r^2} \quad (5)$$

$ß_0$ is determined at the position r = 0. The exponent γr^2 can be replaced by another functions such as γr^m when m>0.

The gap r_{ij} in represented in Eqn(6)

$$r_{ij} = \left\|X_i - X_j\right\| = \sqrt{\sum_{k=1}^{d} x_{ik} - x_{jk}} \quad (6)$$

The applied updated equation is in Eqn(7)

$$\Delta X_i = X_i + ß_0 e^{-\gamma r_{ij}^2}\left(X_j - X_i\right) + \alpha \in_i \quad (7)$$

Here the light intensity is directly proportional to the optimized objective function and vice versa i.e

$I(x) \propto f(x))$FFA is handled by three parameters α, β and γ . The values of γ varies from 0 to ∞. Where the value of β becomes equal to β_0. Beyond these two limiting behavior FFA can be taken in between these factors $i.e. \gamma \to 0$ and $\gamma \to \infty$ Value of α is taken from the interval [0, 1].

The following pseudo code explain the basic structure of the firefly algorithm (FFA):

Algorithm 1:
Input:
Set the population as: $x = (x_{1,} x_2, \dots \dots \dots . x_n)$ with objective function $f(x_i)$
Output:
The best optimized solution is x_{best} whose value $f_{min} = \min(f(x_{best}))$.

1: Initiate the population $x^{(0)} = \left(x_1^{(0)} \dots \dots x_n^{(0)}\right)$;
2: $f\left(x_i^{(0)}\right) = estimate\_current\ \_solution\_\&upgrade\_light\_intensity$;
3: t=0 and γ=1;
4: while $(t < Max\ Gen)$ **do**
5: **for** i=1 to n **do**
6: **for** j=1 to n **do**
7: **if** I(r) i > I(r) j **then**
8: move_firefly_i_towards_j_using_uniform_distribution;
9: **end if**
10: **end for**
11: $f\left(x_i^{(t)}\right)$ = calculate_new_solution_and_update_light_intensity;
12: **end for**
13: select_the_best_one
14: t = t+1
15: **end while**

Basic Particle Swarm Optimization (PSO) Algorithm :

PSO algorithm was developed in the year 1995 [46]. This algorithm is followed with a population (swarm) of particles (i.e candidate's solution) in a particular search space. It is designed with a computational method which optimizes a random problem to update the candidate's solution. The upgraded problem was solved with simple optimized formulas applied across the particle's position and velocity. The movement of each particle is influenced with their known local best (l_{best}) position as well as total swarm's best-known position (global best or g_{best}). Initial position and velocity of each particles in a swarm are updated in a regular manner with PSO algorithm. After each generation we find an optimal solution.

For the optimized solution of PSO algorithm, suppose $(\overrightarrow{s_k})$ be any particle expressed in equation (8) across d dimensional space.

$$\overrightarrow{s_k} = \left\{s_{k1,}\, s_{k2,} \dots \dots \dots . . s_{kd}\right\} \quad (8)$$

Where k=1,2,3….n

Every particle has their own velocities $\overrightarrow{v_k}$ represented in equation (9).

$$\overrightarrow{v_k} = \{v_{k1}, v_{k2} \dots \dots . v_{kd}\} \quad (9)$$

Initially each particle maintain their own (l_{best}) solution and swarm of particles contains g_{best} solution. After each sequential iteration every particles reached towards their optimized goal by updating their previous position and velocity as per the equations (10) and (11).It is optimized that larger the value of w helps for more efficient global search and smaller value of 'w' helps for more efficient the local search [47].

$$\overrightarrow{v_k}(t+1) = w * \overrightarrow{v_k}(t) + c1 * r1 * (\overrightarrow{l_{best}}(t) - \overrightarrow{s_k}(t) + c2 * r2 * \left(\overrightarrow{g_{best}}(t) - \overrightarrow{s_k}(t)\right) \quad (10)$$

$$\overrightarrow{s_k}(t+1) = \overrightarrow{s_k}(t) + \overrightarrow{v_k}(t+1) \quad (11)$$

EFFICIENT PARTICLE SWARM OPTIMIZATION MODEL (EPSO) ALGORITHM.

The operational speed of the basic PSO algorithm is quite slow while searching the global optimum. Efficient PSO is the modified algorithm of the basic PSO which is more helpful for faster search across the global optimum [48].As explained in equation (z) the value of w is taken as constant for all generations. In this modified algorithm the value of w decreases gradually with the increasing number of iterations. This method is followed to reduce the search spaces of the global optimum. After each iteration the worst particle in the present generation would replaced by best particle of earlier generation. In this proposed work two types of selection procedure are followed sequentially to modify the inertial weight these are linear and

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non linear selection. For the linear selection inertial weight w reduces rapidly but across the ideal approach it reduces slowly.

As per the modified algorithm for 1 to $g1$ no of generations the calculated final inertia weight $\lambda 1$ for PSO is calculated from Eq^n(12).

$$\lambda_1 = \lambda_0 - ((\lambda_1/g_1) * i), where\ i = 1,2,3 \dots g_1 \quad (12)$$

For next generation from $g1$ to $g2$ the inertia weight $\lambda 1$ is formulated as Eq^n (13)

$$\lambda_1 = (\lambda_0 - \lambda_1) * \exp(((g_1 + 1) - i)/i), where\ i = g_1 \cdots g_2 \quad (13)$$

Total 100 number of generations are taken here.. With improving the inertial weight we can speed up our process to locate the updated position and velocity of the particle.

Algorithm 2:
For each particle do
Set particle's Initial position and velocity
End for
Until the terminating criteria is not met do
Compute the inertial weight using Eqs. (12) or (13) which depends on generation number
For every particle do
Evaluate the fitness value (Using ANFIS)
If computed fitness value is better than past fitness value (l_{best}) then
Update present position as l_{best}
End if
End for
Select the g_{best} value as the particle with best fitness value among all the particles

For each particle do
Compute particle's velocity using Eq(10)
Update the particle's position using Eq(11)
End for
End while

K- FOLD CROSS VALIDATION

An approach of K-fold cross-validation [49] method is employed in our study. The value of k is chosen as 10.

HYBRID MODEL BASED ON ANFIS-FFA-EPSO

In this model, antecedent's parameters of the ANFIS network consists of the triangular MF parameters, are updated by the FFA and EPSO scheme. The principal emphasis of the ANFIS-FFA-EPSO plot is started initially with basic firefly population randomly, with the goal that every firefly is mapped onto the ANFIS network. Closeness of the fireflies are calculated on the basis of their intensity of light. Simultaneously the EPSO algorithm is used to locate the velocity and position of the selected fireflies from the FFA algorithm .The optimized values (Accuracy, sensitivity, and specificity) which are helpful for effective selection of fitness function in the hybrid model. Figure.8 shows the flow chart of the proposed model.

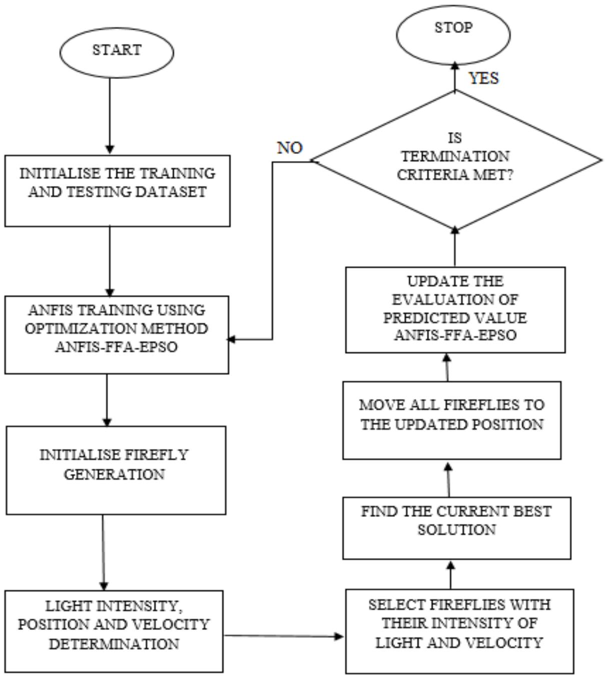

Figure-8. Block diagram of the proposed Model

III. EVALUATION CRITERIA

To evaluate the statistical test data samples are specified into (Positive = classified and negative = misclassified) values which are classified below in Eq^{n}s (14),(15) and(16).

$$Sensitivity = \frac{TP}{TP+FN} * 100 \quad (14)$$
$$Specificity = \frac{TN}{TN+FP} * 100 \quad (15)$$
$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} * 100 \quad (16)$$

IV. RESULTS AND ANALYSIS

Table 2 shows the experimental classification evaluation of different methods using optimizers. .The estimated sensitivity is of 100% of the (ANFIS-FFA-EPSO) method, other values of sensitivities are 99.09 and 99.34 that are calculated from the ANFIS-FFA and ANFIS-EPSO methods respectively. Values of specificity are 98.71%, 97.30% and

96.14% of the methods ANFIS-FFA-EPSO, ANFIS-FFA and ANFIS-EPSO respectively. Estimated accuracies are 99.87%, 98.72% and 98.24% calculated from the methods

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ANFIS- FFA-EPSO, ANFIS-FFA and ANFIS-EPSO respectively. The classified outputs in terms of normal EEG, pre-ictal EEG and ictal EEG is shown in Figure. 9 to Figure. 14. The detected outcomes by Anfis-FFA method is shown in Figure. 9. The classified outcomes by ANFIS-EPSO method is shown in Figure. 10. The outcomes of the proposed method is shown in Figure. 11. The scatter plots of the ANFIS-FFA, ANFIS-EPSO and ANFIS-FFA-EPSO methods are iilustrated in Figure.12, Figure.13 and Figure.14 respectively. Our work in a more clarification form, we are also compared the training dataset output with the different methods as ANFIS-FFA, ANFIS-EPSO and ANFIS-FFA-EPSO outputs. These works are shown in Figure. 15(ANFIS-FFA), Figure.16 (ANFIS-EPSO) and Figure.17 (ANFIS-FFA-EPSO). For validation of our proposed work, ROC analysis and confusion matrix are implemented. The ROC-AUC plot and AUC values for different methods in a magnified form is shown in Figure.18. The confusion matrix of the training data, testing data, validation data and in overally experimental confusion matrix is shown in Figure.19. We are getting validation performance of 0.02322 at epoch 32 as shown in Figure.20. Figure. 21 shows the comparative analysis of sensitivity, specificity and accuracy obtained by ANFIS-FFA, ANFIS-EPSO and ANFIS-FFA-EPSO methods.

Table 3 presents the different estimated observation of Sensitivity, Specificity and Accuracy Maximum Estimated Accuracy achieved from [31] of 99.7% has been calculated by using the method (Entropy with Higher order spectra, Fuzzy sugeno nonlinear features). Maximum sensitivities of 100% is calculated from [28], [31] and [38] with different methods. Maximum specificity of 100% is calculated from [31] and [32] with different methods.The proposed method (ANFIS-FFA-EPSO) shows 99.87% of Accuracy, specificity 98.71%, and sensitivity of 100%.

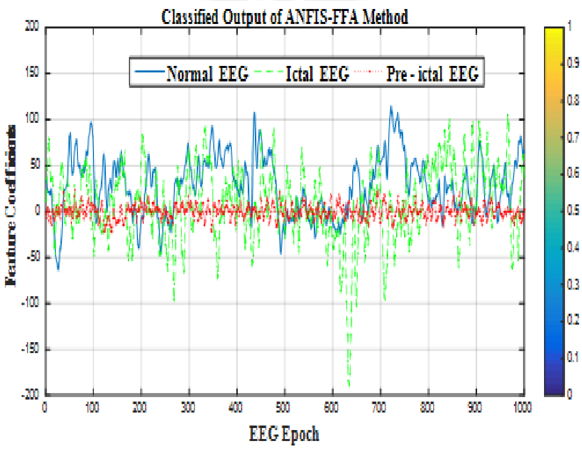

Figure-9: Plot shows the classified outputs of ANFIS-FFA.

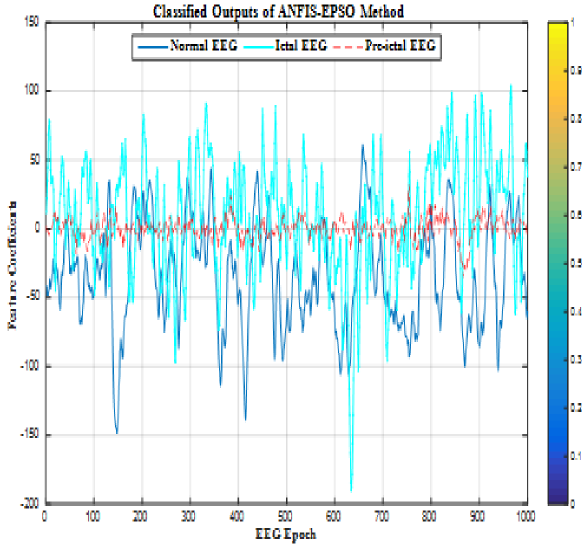

Figure-10: Plot shows the classified outputs of ANFIS-EPSO

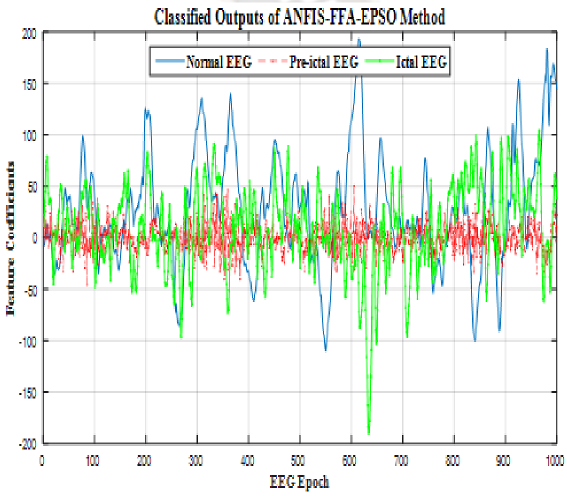

Figure-11: Plot shows the outputs of ANFIS optimized by FFA plus EPSO.

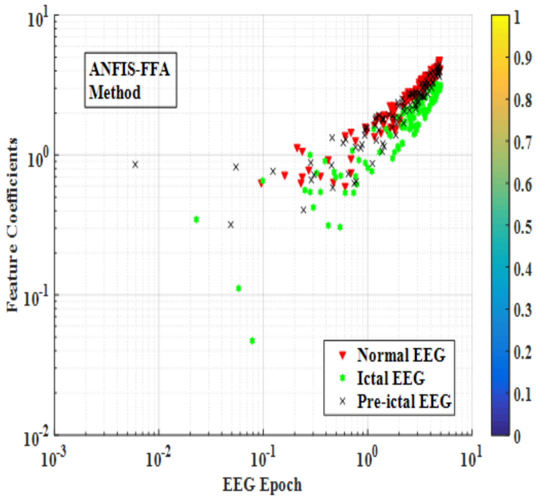

Figure-12: Plot shows scatter form of ANFIS-FFA method.

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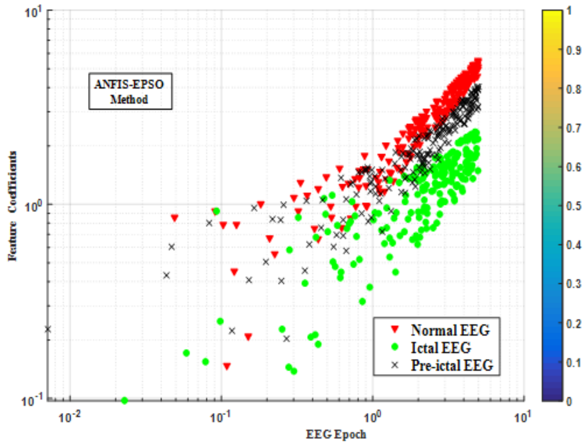

Figure-13: Plot shows scatter form of ANFIS-EPSO method.

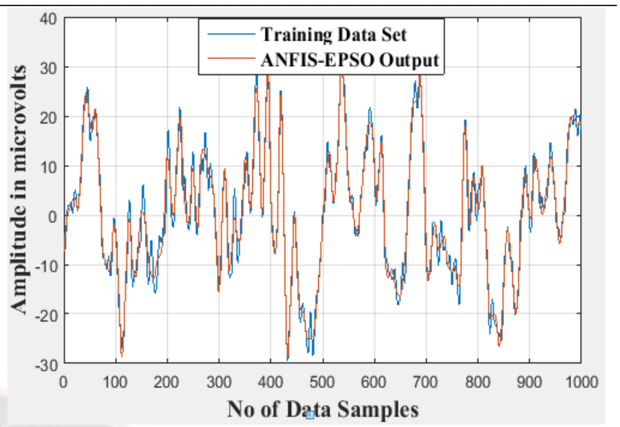

Figure-16: Plot of training data set and ANFIS-EPSO method

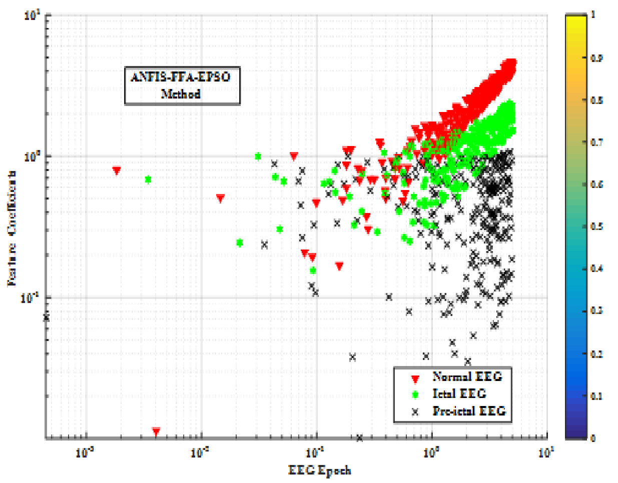

Figure-14: Plot shows scatter form of ANFIS-FFA -EPSO method

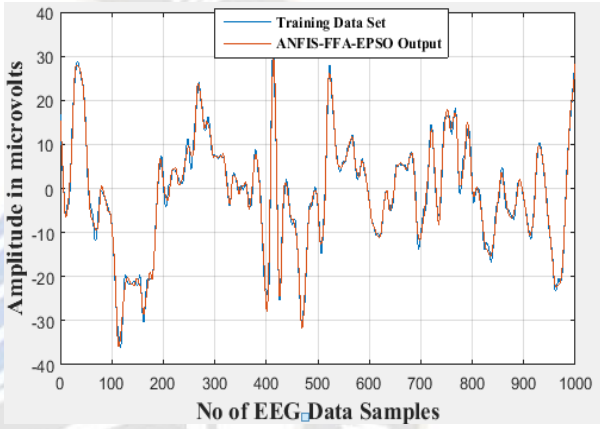

Figure-17: Plot of training data set and ANFIS-FFA-EPSO method

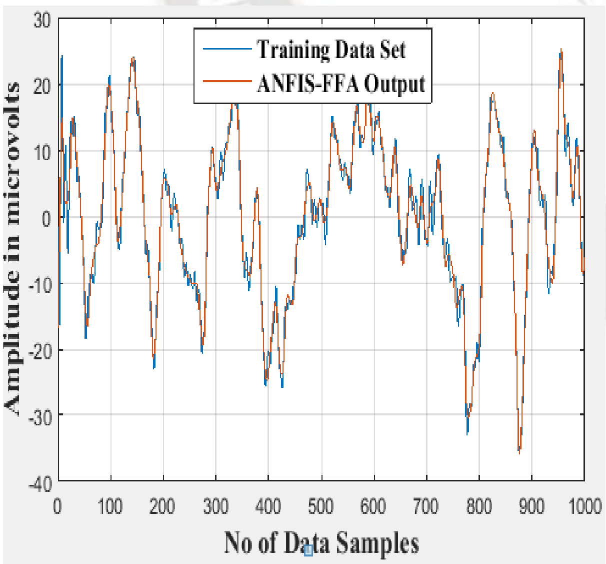

Figure-15: Plot of training data set and ANFIS-FFA method.

Table.2: Classification evaluation of different methods using optimizers.

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
ANFIS-FFA	**98.24**	**99.09**	**96.14**	**0.989**
ANFIS-EPSO	**98.72**	**99.34**	**97.30**	**0-991**
ANFIS-FFA-	**99.87**	**100**	**98.71**	**0.999**

Table-3: Comparative analysis

REF	**METHODS**	**PERFORMANCE ANALYSIS (%)**
[20]	Spike Neural Network (SNN)	ACCURACY: 92.5
[21]	Levenberg Marquardt backpropagation NN ,Wavelet	ACCURACY: 96.7
[22]	PCA,Enhanced Cosine RBF neural network,	ACCURACY: 99.3
[23]	Multi-spiking NN	ACCURACY: 90.7 to 94.8

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[24]	GMM+nonlinear features	SENSITIVITY: 92.2 SPECIFICITYC: 100
[25]	GMM+HOS feature	ACCURACY: 93.1 SENSITIVITY: 97.7 SPECIFICITYC: 92
[26]	GMM	ACCURACY: 93.1 SENSITIVITY: 89.7 SPECIFICITYC: 94.8
[27]	SVM+PSD Estimation	ACCURACY: 93.3 SENSITIVITY: 98.3 SPECIFICITYC: 96.7
[28]	SVM+DWT	ACCURACY: 96.3 SENSITIVITY: 100 SPECIFICITYC: 97.9
[29]	SVM+RQA	ACCURACY: 95.6 SENSITIVITY: 98.9 SPECIFICITYC: 97.8
[30]	KNN+Genetic programming	ACCURACY: 93.5
[31]	Fuzzy sugeno , HOS Features,	ACCURACY: 99.7 SENSITIVITY: 100 SPECIFICITYC: 100
[32]	Fuzzy sugeno, Entropy,	ACCURACY: 98.1 SENSITIVITY: 99.4 SPECIFICITYC: 100
[33]	Fuzzy sugeno, WPD	ACCURACY: 96.7 SENSITIVITY: 95 SPECIFICITYC: 99
[34]	DWT,SVM	ACCURACY: 96 SENSITIVITY: 96 SPECIFICITYC: 97
[35]	EMD, HT	ACCURACY: 95.3 SENSITIVITY: 98 SPECIFICITYC: 97
[36]	Random forest , EMD,	ACCURACY: 99.4 SENSITIVITY: 97.9 SPECIFICITYC: 99.5
[37]	TQWT ,SVM	ACCURACY: 98.6
[38]	LS-SVM, ATFF,WTFD	SENSITIVITY: 100
[39]	Ten-fold cross validation, 13-layer DCNN	ACCURACY: 88.7 SENSITIVITY: 95 SPECIFICITYC: 90
This study	ANFIS, FFA,and EPSO	ACCURACY: 99.87 SENSITIVITY: 100 SPECIFICITY: 98.71

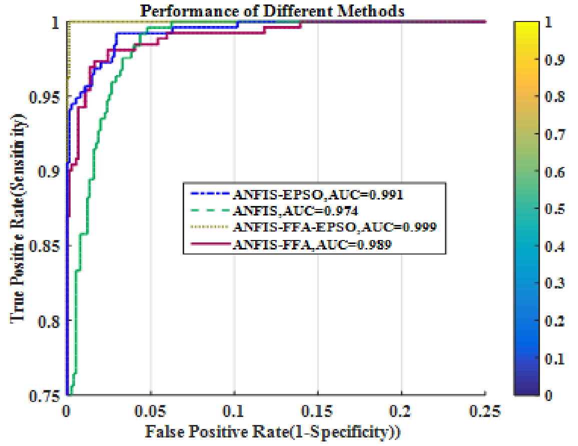

Figure 18. ROC –AUC plot and AUC values for different methods.*(Here the plot is magnified to distinguish the curves)*

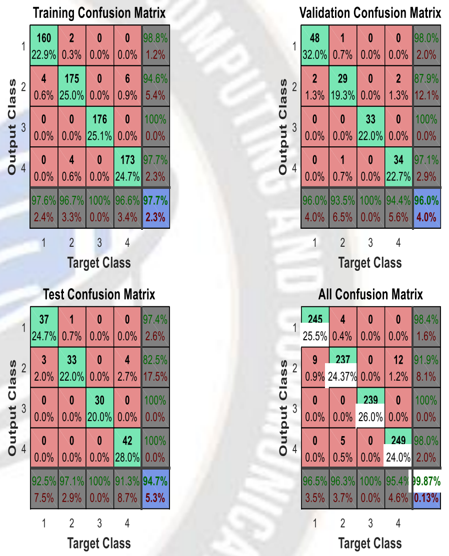

Figure-19. Confusion matrix of the proposed experimental analysis

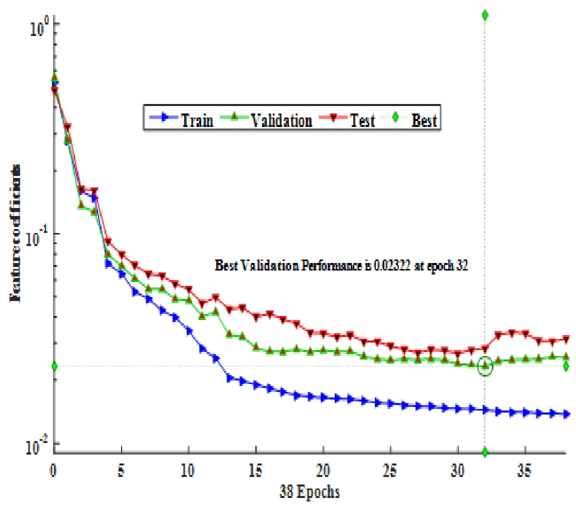

Figure-20 Plot shows the best validation performance at epoch 32

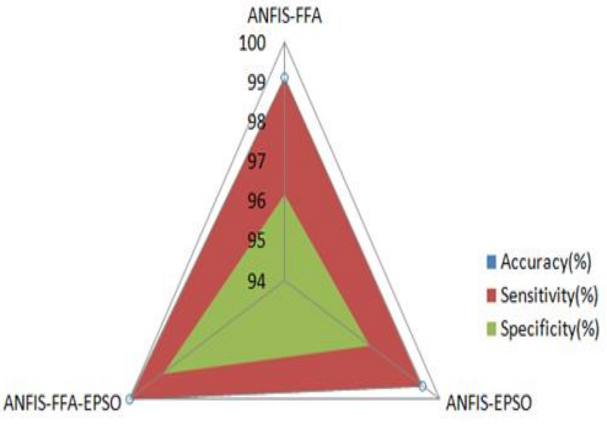

Figure-21: Plot shows comparative analysis between different statistical parameters

V. Conclusion and Future Work

In this work, an ideal hybrid method is used to train the ANFIS network. Two nature inspired algorithms such as firefly algorithm and efficient PSO algorithms are jointly used as optimized algorithm to train and test the ANFIS Network. This hybrid method classify the seizure and non-seizure signals with a higher Accuracy as compared to the existing methods that are optimized from same database. From our experimental observation we have concluded that FFA and EPSO algorithms can optimized ANFIS network and classify the EEG signals. The SENSITIVITY of 100%, SPECIFICITY of 98.71%, ACCURACY of 99.87 %, are achieved on the patient specific database from Bonn University,The oAut performance of the method (ANFIS-FFA-EPSO) is clearly mentioned under the ROC .

Future Work : Future work includes : Conduction of experiments in long term EEG segments; detection of post-ictal and interictal EEG signals, implementation of feature extraction and extreme machine learning algorithms to enhance the statistical performances.

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