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Research paper

Detection and Classification of Genetically Transfered Idiopathic Partial Epilepsy to Child:a Four Rule ANFIS based SWT-EBFO Approach

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Abstract

Background:-Hereditary qualities have an influence in numerous sorts of epilepsy. In the event that a parent has idiopathic epilepsy, there is around 5% to 8% chance that the youngster upto 8 years will likewise have epilepsy called as idiopathic partial epilepsy (IPE).
Methods:-This exploration work breaks down the epilepsy issue exchange hereditarily by coordinating the best properties of Enhanced Bacterial Foraging Optimization (EBFO) and Least-mean-square (LMS) algorithm with four rule Adaptive Neuro-fuzzy Inference System (ANFIS) Network. Stockwell Transform (SWT) strategy searched for the extraction of decomposed signal. In this work, quantitative tests and statistical tests are performed by utilizing SWT-ANFIS-EBFO and SWT-ANFIS-LMS strategies.
Results:-Our proposed statistical results(Accuracy (98.30%), sensitivity (98.23%), specificity (99.53%) and Matthew's correlation coefficient (97.08%),G-mean (98.88%) and average detection ratio (98.93%)) are calculated withthe network SWT-ANFIS-LMS. Proposed statistical results (accuracy (99.49%), sensitivity (98.78%), specificity (98.56%), and Matthew's correlation coefficient (97.907%), G-mean (99.172) and average detection ratio (99.174%)) are calculated SWT-ANFIS-EBFO beats. The calculated quantitative test results for network SWT-ANFIS-LMS are (SNR 18.42±0.18, RE 0.11±0.02, CC 61±0.012, MFRE 0.41±0.02) and for network SWT-ANFIS-MFRE are (SNR 18.42±0.18, RE 0.11±0.02, CC 61±0.012, MFRE 0.41±0.02).
Conclusion:-In this paper we endeavor to investigate the best capability of SWT based ANFISnetwork trained with EBFO and LMS algorithms for classification of IPE EEG signals.Calculated statisticaland quantative test results of the proposed method outperforms as compared to existing methods. It will end up being a significant trial device in clinical application and advantageous application towards IPE influenced patients.

***Keywords**: IPE, EBFO, LMS, SWT, ANFIS.*

1. Introduction

Presently the specialists are attempting to know the hereditary factors in epilepsy. These components may incorporate the transformations and chromosomal deformities. As per Mendelian rule, the idiopathic epilepsy is a quality related epilepsy which is transmitted from mother to her child. So it is important to distinguish the Idiopathic Epilepsy in mother and the transmitted epilepsy from mother to her kid known as idiopathic partial epilepsy for appropriate determination. Ailments of the cerebrum portrayed by a persisting inclination to create epileptic Seizures are known as epilepsy [1-2]. Time recurrence signal handling procedures, for example, Discrete Wavelet Transform (DWT) [3, 4], have been broadly used to give a quantitative measure of the recurrence circulation of the EEG and identify the nearness of specific examples. The diverse machine learning methods utilized for grouping are Artificial Neural Network [5-12],support vector machine [13] Radial Basic Function Neural Network[14],etc. The improved design of RBF neural system snatches more
Consideration for upgrading its precision in order of EEG signals [14, 15, 16]. Among these arrangement strategies ANN is most prominent one due its propelling properties of self-learning, versatility, and strength. A scope of ANN-based methodologies have been accounted for in the writing on epilepsy refinement [17-20]. In an observation [21], the decomposed registered in EMD-DWT area are effectively utilized for the segregation and classification of F and NF EEG signals. The EMD strategy is information subordinate system which deteriorates a signal by assessing the envelope from maxima and minima introduce in the signal. In actuality, the DWT decays a signal in to sub-groups utilizing a predefined premise work. The highlights removed from DWT decay of the EEG signals are additionally observed to be effective for the investigation of the F and NF EEG signals [22]. In [23], the time-recurrence restricted wavelets are utilized for the classification of F and NF EEG signals. In another experiment [24], time-recurrence confined three-band biorthogonal wavelet filter bank is utilized to dissect epileptic EEG signals [25]. It is appeared in the past investigations that the data identified with the epileptic movement is appropriated in different DWT sub-groups [25, 26].
From the writing, it is watched that classifiers of signal organize are probably going to be actualized in the majority of the examinations, and there is uncommon of earlier strategies identified with the extraction of ANFIS prepared with PSO, particularly for EEG signals handling. Its essential property is its computational effortlessness, which makes it conceivable to break

down signs in testing pragmatic applications. This paper depicts a novel composite strategy for IPE epilepsy through various time recurrence changes, for example, SWT. The component extraction method by utilizing above changes independently, the yield is observed by utilizing four rule ANFIS network prepared with anEnhanced Bacterial Foraging Optimization (EBFO), Least-mean-square (LMS) algorithm and stock well transform. The execution of the order procedure is estimated by limit in distinguishing epileptic seizures from the information. To the best of our insight, this is the main work to check such changed and non-changed signals independently with SWT-ANFIS-EBFO, SWT-ANFIS-LMS and arrange them for IPE patients for early clinical analysis.

2. Materials and Methods

2.1. Materials

The EEG dataset utilized in this work was obtained from the database of University of californiainvine knowledge (UCI KDD) file. It is accessible online at http://kdd.ics.uci.edu/databases/eeg/eeg-data.html. The informational index was obtained to investigate connection between EEG Signals and the hereditarily exchange of seizure IPE. Dataset incorporates the EEG recordingsof kids between ages 5 and 8 having epilepsy. These EEG signals contain occasion related bio-potentials got by 31 anodes that were connected on the scalp of the mind. The EEG signals were recorded for 30 second with top having 28 lead anode. The framework was having a testing recurrence of 173.61 Hz and 12 bit determination .The EEG signals with undesired and 30 accounts for each IPE class were considered. Every one of these EEG signals has 2000 data recorded for 30 seconds.

2.2. Methods

2.2.1. Stockwell Transform(Swt)

As EEG signal contains multiple spectra of clinical data, it is required to break down the typical EEG and influenced EEG because of epilepsy. Stockwell Transform(SWT) distinguishes the nearby amplitude and power spectrum [27] perfectly. SWT is better than contineous wavelet transform [28]. The Stockwell transform $s_x(\tau, d)$ of EEG signals x(t) is characterized as :

$$w_x(\tau, d) = \int_{-\infty}^{+\infty} x(t) w(t-\tau, d) dx \tag{1}$$

$$s_x(\tau, d) = e^{j2\pi f\tau} w_x(\tau, d) \tag{2}$$

Where $w_x(\tau, d)$is the wavelet transform of signalx(t) and the mother wavelet $w(t, \tau)$ is choosen as follows

$$w(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}} e^{-i2\pi ft} \tag{3}$$

where factor d is the inverse of frequency f. By applying Eq. (3) to Eq. (1), we obtain the Stockwell transform $s_x(\tau, f)$of signal x(t) shown as follows:

$$s_x(\tau, f) = \frac{|f|}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} e^{\frac{-(\tau-t)^2 f^2}{2}} e^{-2\pi ift} x(t) dt, \quad \tau, f \in R \tag{4}$$

The width of the Gaussian window in Eq. (4) is determined by the inverse of frequency f.

2.2.2. Bacteria Foraging Optimization (BFO) Technique

Bacteria foraging optimization (BFO) is one of the improved optimization strategy in view of the scrounging idea of genuine bacteria organisms [29]. Microscopic organisms perceive the way of nourishment in view of the angles of chemicals in their condition and emit pulling in and repulsing chemicals into the earth in same way to see others on that way. Systems like tumbling and turning through which microorganisms can move are alluded as swimming. There are just two fundamental movements known as tumble and swim that microscopic organisms take after to reach at great supplements condition for their survival. Tumbling is identified with alter of the course of movement to discover great supplement put, while swim is the means taken after the tumble when a bearing is chosen. These procedures of tumble and swim are all in all known as chemotaxis that is trailed by every bacterium. End and multiplication are required to murder those microbes, which can't get out from awful supplement condition (poisonous) and create new microscopic organisms(bacteria) to adjust the populace [29]. Streamlining calculation inferred in view of the microscopic organism's survival methodology enables bacteria's cell in stochastic process. Arrangement of three principle forms on a populace of determined cells are performed to imitate genuine microorganisms conduct:
(a) Chemotaxis: For this situation, the cost of cells is resolved in view of target capacity, and cells move along the controlled course and separation between tumble and swim. Most of crafted by the calculation lives in this procedure.
(b) Reproduction: This procedure, just contains those cells that performed better in their lifespan may add to create the updated solutions of new generation.
(c) Elimination-dispersal: cells of this progression, are disposed of and new random arrangements are created with a low likelihood to adjust the span of population.
Essential wording utilized as a part of BFO calculation with the principle working condition (Eq(5)) in charge of chemotaxis process is explained below:
j, k and l are the list for the chemotactic step, multiplication step and termination dispersal step individually. The accompanying parameters contains their usual meaning are fixed before instating the loop as :P is the dimension of hunted positional space , S is the Number of microorganismsi.e bacteria,N_c isthe total number of chemotactic steps , N_s is the swimming length i.e bacterial developments inside one chemotactic cycle ,$S_r$is the total number of bacteria's reproduced in the population, N_{re} is thetotal number of proliferation (reproduction) levels, N_{ed} is number of elimination dispersal and P_{ed} isprobability of elimination dispersal .
Above documentations are deciphered with cycles as: P(j, k, l) {(j, k, l)|i 1, 2, … , S}, where i=q is the positional arrangement of every element(member) in the number of inhabitants in the S bacteria at the j^{th} chemotactic step, k^{th} multiplication step, and l^{th} is the elimination dispersal stages. Here, let J (I, j, k, l) indicates the cost at the area of the i-th bacterium. The fundamental and predominance frame work in chemotactic process is displayed as Eq. (5),

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + c(i) * dct_i$$

$$\text{Where} dct_i = \frac{\delta(i)}{\sqrt{\delta^i(i)\delta(i)}} \tag{5}$$

Here,δrepresents the vector in the arbitrary directionwithin the values between -1 and 1 for i^{th} bacterium position as θ^i, j, k, and l are the guided index of the above said method described above.$c(i)$is the step length of bacteria i in a random dimensions (dct_i) ,

2.2.3. Enhanced Bacterial Foraging Optimization (Ebfo)

The IBFO system was developed by consolidating Opposition Based Learning (OBL) with the first BFO calculation. OBL was first proposed by Tizhoosh [30]. The OBL technique creates relating inverse answers for each underlying applicant arrangement. From these two sorts of arrangements (applicant

arrangements and comparing inverse arrangements), the arrangements with moderately better wellness are chosen as individuals from the underlying populaces. This will enhance the merging rate in the advancement procedure. The related numerical ideas of the OBL procedure can be spoken to as takes after.
Let x ∈ R be a genuine number characterized on a specific interim: $x\epsilon[a,b]$The contrary number $\breve{x}$ is characterized as takes after:

$$\breve{x} = a + b - x \quad (6)$$

$p(x_1, x_2, \ldots\ldots x_n)$ Bethe point insidean n-dimensional coordinate facilitate framework with$x_1, x_2, \ldots\ldots x_n \epsilon R$ and $x_i[a_i, b_i]$ points. The characterized oppositepoint P∗ is totally defined by its directional coordinates x_1*,x_2*…….x_n* where

$$x_i^* = a_i - b_i - x_i \; w\square ere \;\; i = 1,2, \ldots . n \quad (7)$$

Let $f(x)$be the primary function and $g(.)$ is appropriate assessment function. If the event$x\epsilon[a,b]$ is considered asa primary random figure and x^* represents its contrary estimated value, then after in each iteration stages we calculate the $f(x)$and$f(x^*)$. The method of learning proceeds with x if condition $g(f(x)) \geq g(f(x^*)$satisfied. The underlying arrangements of bacterial populaces can be communicated as:

$$x_i = x_{low} + rand(x_{up} - x_{low})\text{Wherei=1, 2…..n} \quad (8)$$

Where S is the swarm size of the populace. The relating inverse arrangements x_i^* of bacterial populaces in light of restriction based learning can be communicated as
$x_i^x = x_{up} + x_{low} - x_i(9)$

Algorithm of EBFO

Stage 1: Initialize all the parameters S, N_s, N_c, N_r, N_{ed}, C(i), and P_{ed},and the initial bacteria positions inside enquiry searchspace are characterized.
Stage 2: looping: l=l+1. For the Elimination-dispersal
Stage 3: looping: k=k+1. ForReproduction
Stage 4: looping: j=j+1 for Chemotactic
i=1: S (corresponding each bacterium), perform chemotacticmethod through Eq**. (9)** on a greatest of Ns bacterial development with movement.First development is always a tumble process for this δ(i)is randomly selected.
Stage 5: Ifj<Nc, move to Step 4. In this situation proceed, chemotacticsince the life of the bacteria is not finished.
Stage 6: Reproduction system (in k stages loop): sort the bacteria populationbased on their health accumulated during all chemotactic stages. The S/2 bacterium with best qualities remains andsplits, with the copies being put at an indistinguishable area from their parent.
Step 7: Ifk $<$ N_r, go to Step 3. Number of identified reproductionlevel not reached and begin the updated next generation of thechemotactic loop.
Step 8: Elimination-dispersal: with probability P_{ed}wipe out and scatterand disperse every bacterium in the population. Replacement ofbacterium to a random location on the optimization domain is done. If $1 < n_e$, then go to Step 2; otherwise, end.

2.2.4. Least-Mean-Square (LMS) Algorithm

LMS calculation is the most broadly utilized algorithm in versatile adaptive filtering and classification because of its low computational complexity [31, 32]. In this calculation, estimation of error and weights updation are done through Equations (10) and (11), separately.

$$e(n) = d(n) - y(n) \quad (10)$$

$$w(n+1) = w(n) + 2\mu e(n)x(n) \quad (11)$$

Where, $x(n)$ is the vector of sources of information related to signal correlation,$d(n)$ is meant as the estimated desired signal.$y(n)$is the estimate of the desired signal ascertained as $y(n) = x^T(n)w(n)$and $e(n)$ is the estimated error, while $w(n)$ is the weight vector at nth cycle, and the parameter m is the union factor that controls the convergence rate.

3. Our Proposed Method

This work depicts and dissects a composite technique for order of electroencephalogram (EEG) signals in light of an arrangement of highlights separated from different time-recurrence changes. According to [33] ANFIS display is utilized to manage arrangement and control issue. In this paper 4-Rule ANFIS classifier is utilized and assessed over a collection of signals. This classifier ordered into training informational collection and testing informational collection. The preparation informational collection is utilized for preparing the exactness of the proposed display for the grouping of IPE signals. Here the ended parameters of the participation capacities are orchestrated to refresh according to the underlying parameters. In our work ANFIS organize is prepared with Bell membership function. The stream of the proposed procedure are represented in figure 3.
The recorded IPE signals are influenced by instrumental and organic commotions which are inputted to stock well transformer. The highlights like least, most extreme and mean of the supreme estimations of the co-efficient in each flag were separated. Additionally the standard deviation and normal energy of the wavelet co-efficient in each signal were separated. In this technique an altered rendition of modified genetic algorithm is utilized to prepare the 4-basic ruled ANFIS Network for legitimate characterization of typical EEG Signal and IPE influenced EEG Signal of youngster. Additionally to arrange between ordinary EEG signal and IPE influenced EEG signal of beneath 8 years children. The four rule based ANFIS network is further trained with the two advance algorithms as EBFO and LMS algorithm.

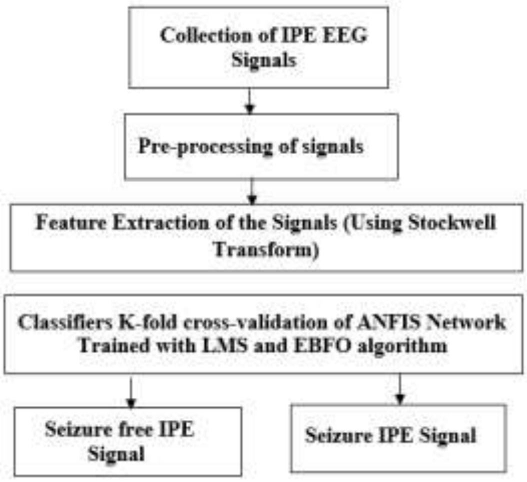

Figure 1: Block Diagram of Proposed Model

4. Evaluation Criteria

4.1. Quantitative Test

In our paper, different quantitative criteria such as Signal to noise ratio, relativeerror, correlation coefficients and mean frequency relative error are calculated. The SNR can be obtained by equation (12):

$$\mathrm{SNR} = 10\log_{10}\frac{\mathrm{var(s(k))}}{\mathrm{var(s(k)}-\hat{s}\mathrm{(k))}} \quad (12)$$

Where, var $s(k)$and $\hat{s}(k)$ are the difference operator. Equation(13) is utilized to compute the RE, which is a lower estimation of the RE compares to a superior execution. $P_S(f)$ and $P_{\hat{s}}(f)$are the power unearthly thickness (PSD) of s(k) and ŝ(k)

$$\mathrm{RE} = \frac{\sum\left(\mathrm{P_S(f)-P_{\hat{S}}(f)}\right)}{\sum(\mathrm{p_s\,(f)})^2} \quad (13)$$

A diminishing of relative error compares to better execution isused to ascertain the Correlation Coefficients is,

$$\mathrm{CC} = \frac{\sum \mathrm{S(K)+\hat{S}(K)}}{\sqrt{\sum \mathrm{s(k))^2} \sum(\hat{s}\mathrm{(k)})^2}} \quad (14)$$

MFRE was performed by calculating the entire difference between mean frequency of the conventional EEG and mean recurrence of the denoised EEG signals utilizing repetition clamor expulsion techniques and were partitioned by mean recurrence of the basic EEG. A lower estimation valueof the MFRE compared with a better executed result.

4.2. Statistical Test

Samples correctly classified and misclassified are labeled, respectively, as True Positive (TP) and False Negative (FN). On the other hand, samples of other class can be classified as True Negative (TN) or false positive (FP). These outcomes are expressed in terms of sensitivity or True Positive Rate (TPR), specificity or True Negative Rate (TNR), accuracy and Matthew's correlation coefficient, Average Detection Ratio (ADR) and G-meanas:

$$\text{True Positive Rate(Sensitivity)} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \quad (15)$$

$$\text{True Negative Rate (Specificity)} =\frac{\mathrm{TN}}{\mathrm{TN+FP}} \quad (16)$$

$$\text{Accuracy}\,\frac{\mathrm{TN+TP}}{\mathrm{TN+TP+FN+FP}} \quad (17)$$

Matthew's correlation coefficient

$$\mathrm{MCC} = \frac{\mathrm{TP*TN-FP*FN}}{\sqrt{\mathrm{(TP+FN)(TP+FP)(TN+FN)(TN+FP)}}} \times 100 \quad (18)$$

The expression for G-mean is $=\sqrt{\mathbf{SEN} * \mathbf{SPE}}$ (19)

Average detection ratio (ADR) is expressed as:

$$\mathbf{ADR} = \frac{\mathbf{SEN+SPE}}{\mathbf{2}} * \mathbf{100} \quad (20)$$

5. Result and Discussion

Every one of the examinations were directed under the field of MATLAB R2017a. In this examination, a hereditary exchange of epilepsy from mother to kids is grouped for legitimate diagnosis. In our work idiopathic partial epilepsy of child are tentatively recorded. The Raw EEG for limit is taken from database. For exploratory investigation of epilepsy, ten number of IPE patients were picked. The quantitative and statistical tests are figured by utilizing SWT-ANFIS-LMS and SWT-ANFIS-EBFO strategies independently and compared and other existing techniques.

The cross-endorsement was performed using K-folds approval with K =10. This methodology is moreover called unrest assessed strategy. In this measurable data separating strategy, the mother instructive accumulations are subdivided into K sub-sets. From these subsets, certain sets are kept aside for later testing of the classifier's execution, and hence, are called preparing sets, while whatever is left of the sets are at first used for setting up the classifier show and are, in like manner, called testing sets. As we would see it is kept comparable to 1:9 proportion. This inferred out of the 10 sub-sets allotted, only 1 set is used for getting ready and the rest 9 sets are used for testing reason.

Table 1 and 2 Shows the quantitative and stastical estimation of SNR,RE,CC, and MFRE by utilizing four rule based ANFIS network prepared with EBFO and LMS algorithm with stockwell transform. From table 1 we conclude that the stockwell transform with four rule ANFIS network trained with EBFO performs better result(with SNR 18.42±0.12, RE 0.10±0.03,CC 61±0.012, MFRE 38±0.01) as compared to the ANFIS network trained with LMS and BFO algorithm.Table 4 and 5 and demonstrates a comparative estimation of Sensitivity, specificity, Accuracy approaches with various existing techniques. For stock well transforms used with ANFIS-LMS network different calculated statistical average values are accuracy (98.30%), sensitivity (98.23%), specificity (99.53%) , and Matthew's correlation coefficient (97.08%),G-mean (98.88%) and average detection ratio (98.93%) shown in table 2.The average accuracy (99.49%), sensitivity (98.78%), specificity (98.56%) , and Matthew's correlation coefficient(97.907%),G-mean(99.172) and average detection ratio(99.174%) for stock well transforms with ANFIS-EBFO network are getting outperform as compared to with existing methods as shown in table 3.From the calculated test result for IPE affected patients, the proposed strategy is valuable for characterization of seizure because of epilepsy detection helps in determination of children having epilepsy. . The calculated quantitative test results for network SWT-ANFIS-LMS are (SNR 18.42±0.18, RE 0.11±0.02, CC 61±0.012, MFRE 0.41±0.02) and for network SWT-ANFIS-MFRE are (SNR 18.42±0.18, RE 0.11±0.02, CC 61±0.012, MFRE 0.41±0.02).

The proposed approach has two primary favorable circumstances: one is to use the combination of SWT as highlight extraction, while another comes to work of four rules ANFIS trained with EBFO and LMS optimization algorithm. This approach will be reasonable method of solution for broad clinical approval of idiopathic partial epilepsy patients as far as the steady structure and predominant execution. Likewise from figure (3-4) demonstrates the comparative plot between IPE output signal with SWT-ANFIS-LMS output and IPE signal with SWT-ANFIS-EBFO outputseparately. From this we conclude that SWT-ANFIS-EBFO system can be utilized as a composite classifier for appropriate determination of seizure display in EEG signal of idiopathic partial epilepsy influenced child.

6. Conclusion

In this work ,the issue of genetically change of epilepsy from mother to her kid has been had a tendency to by displaying differing component extraction procedures autonomously using 4-lead ANFIS classifier arranged with another Enhanced Bacterial Foraging Optimization (EBFO).The results show that the proposed system is wound up being more target, convincing and stable . The execution of our classifier arranged with modified Genetic Algorithm and feature extraction designs has been settled and stood out from that of the present works. According to the results, the stockwell change with ANFIS-EBFO procedures beats than the present strategies. We in this way complete up as the test outcomes suggest, the proposed system can reduce the pros of the heaviness of visuality surveying a sweeping volume of EEG data and generally quicken the clinical conclusion in starting time of IPE patients.

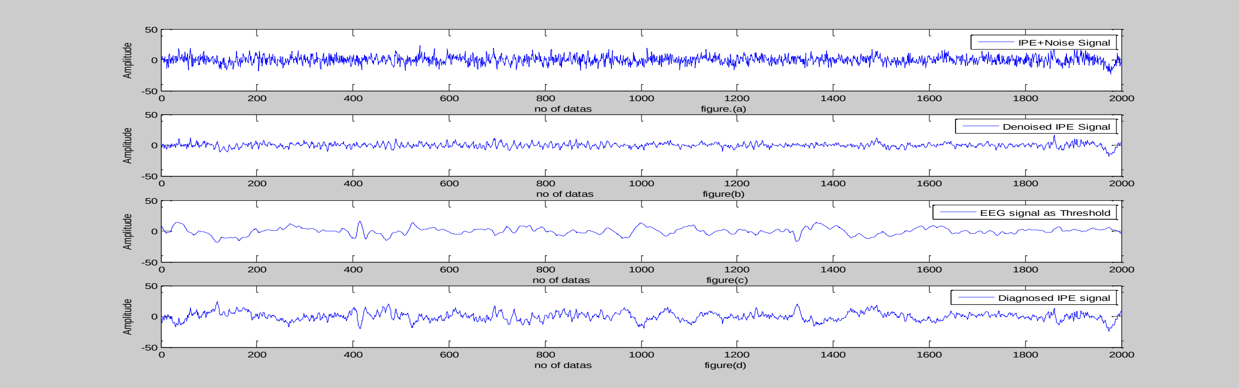

Figure 2: (a) Recorded IPEsignal of child having epilepsy with noises.(b) denoised IPE signal (c) Raw EEG signal from database as threshold (d) classified IPE EEG signal.

Table 1: Quantitative test results of different parameters for IPE patients (child).

Method	SNR (dB)	RE	CC	MFRE
SWT-ANFIS	13.69±0.21	0.19±0.03	0.30±0.01	0.72±0.05
SWT-ANFIS-BFO	15.84±0.23	0.15±0.02	0.47±0.03	0.62±0.02
SWT-ANFIS-LMS	18.49±0.18	0.11±0.02	0.53±0.02	0.41±0.02
SWT-ANFIS-EBFO	18.42±0.12	0.10±0.03	61±0.012	38±0.01

Table:-2: Stastical: test results of different parameters for 10 IPE patients using method (SWT-ANFIS-LMS).

Sl. No	TP	FN	TN	FP	ACC	SEN	SPE	G-Mean	MCC	ADR
1	1624	17	14653	44	99.6266	98.9640	99.7006	99.3316	97.9528	97.6028
2	4248	184	29064	188	98.8956	95.8483	99.3573	97.5870	95.1692	99.3648
3	2620	12	36107	45	99.8530	99.5440	99.8755	99.7096	98.8472	98.8659
4	13320	89	1104	18	99.2636	99.3362	98.3957	98.8648	95.0311	99.5282
5	3214	27	38022	42	99.8329	99.1669	99.8896	99.5276	98.8476	99.3062
6	6372	64	19457	181	99.0603	99.0055	99.0783	99.0419	97.4952	99.7560
7	3971	37	51030	42	99.0565	99.0768	99.9177	99.4964	98.9377	98.6359
8	1630	41	25076	69	99.3897	97.5463	99.7255	98.6299	96.5208	97.8707
9	912	38	22382	58	99.5895	96	99.7415	97.8528	94.7916	98.7481
10	5417	119	41357	147	98.4345	97.8504	99.6458	98.7440	97.2834	99.6300
avg					99.30	98.23	99.53	98.88	97.08	98.93

Table: - 3: Stastical test results of different parameters for 10 IPE patients using method (SWT-ANFIS-EBFO).

Sl. No	TP	FN	TN	FP	ACC	SEN	SPE	G-Mean	MCC	ADR
1	1592	19	14688	39	99.6450	98.8206	99.7351	99.2768	98.0162	99.2778
2	4381	169	28997	137	99.0915	96.2857	99.5297	97.8943	96.1014	97.9077
3	1502	18	8421	36	99.4587	98.8157	99.5743	99.1943	97.9169	99.1950
4	2515	17	12291	41	99.6098	99.3285	99.6675	99.4979	98.6262	99.4980
5	9225	37	18477	187	99.1978	99.6005	98.9980	99.2988	98.2051	99.2992
6	6448	69	19406	151	99.1562	98.9412	99.2279	99.0844	97.7624	99.0845
7	2870	8	32736	77	99.7618	99.7220	99.7653	99.7436	98.4193	99.7436
8	7832	19	10748	47	99.6460	99.7579	99.5646	99.6612	99.2748	99.6613
9	3892	34	51102	52	99.8438	99.1339	99.8983	99.5154	98.8234	99.5161
10	1620	42	25067	87	99.5189	97.4729	99.6541	98.5574	95.9241	98.5635
average					99.4929	98.7878	99.5615	99.1724	97.9070	99.1747

Table 4: A comparative analysis of accuracy between proposed method and various existing methods used for epilepsy detection.

Reference	**Methods**	**Accuracy(%)**
[34]	Entropies based fuzzy	98.10
[35]	EA,NNE followed with DWT	98.78
[36]	TQWT based correntropy and LS-SVM	97.02
[37]	EMD based SODPand ANN	97.75
[38]	linear prediction error energy	94
[39]	fractional linear prediction(FLP)	95.33
[40]	Stockwell transform based to boosting algorithm	98.30
[41]	SVM followed to wavelet Transformation	95.33
[42]	Gabor filters follwed to nearest neighbor classifier	98.33
[43]	Wavelet Transform with PSR, NEWFM	98.17
[44]	Cross-correlation aided support vector machine	95.5
[45]	RWE+ ANN	95.2
[46]	wavelet feature extraction based mixture of expert model	94.5
[47]	FLP + Support Vector Machine	95.33
[48]	HMS Analysis with Support Vector Machine	98.80
[49]	TQWT,KE and LS-SVM	97.75
[50]	DTCWT,ESD,entropy With Neural Network	99.15
[51]	EMD + LS- Support Vector Machine	97.75

Proposed Method	SWT-ANFIS-LMS SWT-ANFIS-EBFO	99.30 99.49

Table 5: A comparative analysis between proposed methods sensitivity and specificity measurement with various existing methods to epilepsy detection

Reference	Methods	Sensitivity(%)	Specifisity(%)
[40]	Stockwell transform and boosting algorithm	94.26	96.34
[41]	WT and SVM Seizure detection	94.46	95.26
[43]	Wavelet transform, phase space reconstruction, Euclidean distance based on NEWFM	96.33	100
[44]	Cross-correlation aided support vector machine	92.4	98.6
[45]	RWE with ANN	98.17	92.12
[46]	wavelet feature extraction based mixture of expert model	95	94
[47]	Fractional linear prediction,SVM	96	95
[49]	TQWT,Kraskov entropy and LS-SVM	97	99
[50]	DTCWT,energy, standard deviation,entropy and General regression neural network	98.32	99.55
[51]	EMD and LS-SVM	97.68	98.07
Proposed method	SWT-ANFIS-LMS SWT-ANFIS-EBFO	98.23 98.78	99.53 99.56

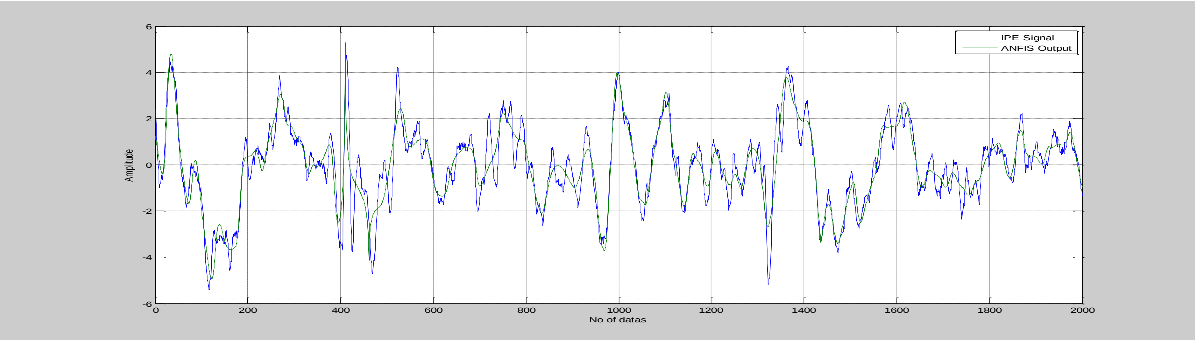

Figure 3: Comparative plot of IPE signal with SWT+ANFIS-LMS Output.

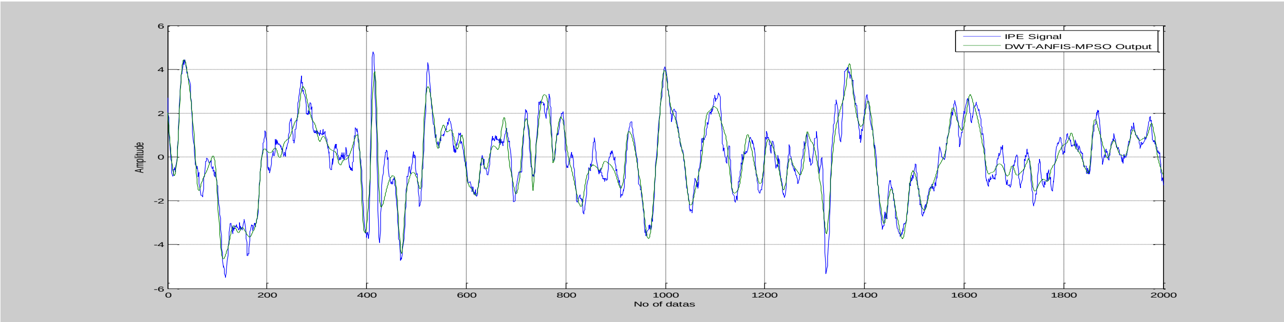

Figure 4: Comparative plot of IPE signal with SWT-ANFIS-EBFO Output

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