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A Hybrid and Automated Epileptic Seizure Detection Model using Improved PSO and Extreme Learning ANFIS Network

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Abstract: ***The main aim of the proposed work is to generate an accurate automated seizure detection model for the performance evaluation of the improvement on epileptic patients in an improved manner. Long data sets of EEG signals are recorded for a long duration of time which has taken from PhysioNet CHB-MIT EEG datset for this experimental work. Six types of elements are excerpted from EEG signals by using WPT method and which is then classified by using CFS method. Then, all the features are combinely inputted to the rule based twin- support vector machines (TSVM$_s$) to detect normal, ictal and pre-ictal EEG segments. The developed seizure detection WPT-KWMTSVM method achieved excellent performance with the average Accuracy, specificity, sensitivity, G-mean, positive predictive value, and Mathews correlation coefficients are 97.14%, 97.33%, 97.00%, 97.31%, 96.85%, 95.96% respectively The average area under curve (AUC) is approximately 1. The proposed method is able to enhance the seizure detection outcomes for proper clinical diagnosis in medical applications.***

Keywords: ***EEG Signal, Epileptic Seizure, IPSO WPT, ELANFIS, MLPNN, RBFNN, ANFIS***

I. INTRODUCTION

Epilepsy is the leading neuronal abnormality of the brain, produced by concurrent disorder of a clutch of neurons which disturbs millions of human beings in the whole world [1]. The large data sets of EEG signals must be observed for a long duration of time for proper identification and analysis of epileptic seizures. For monitoring of Electroencephalogram signals of the patient's is very much monotonous and long delayed process. Along with that, the recorded EEG signal may get affected by various types of noise. Therefore, a real time monitoring and therapeutically automatic seizure detection method may be proposed.

In [2] Rafiuddin et al. in the year 2011, developed an automated epileptic seizure detection method using 23 numbers of channels on 23 numbers of patients.

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In this research work, various statistical parameters are calculated from Electroencephalogram signals those are extracted from
Wavelet coefficients. The experimented outcome in the form of Accuracy is 80.16%.

Khan et al. [3] designed an EEG seizure detector in the year 2012. In this research, 80% of EEG data are used for training. The relative values of energy are computed from wavelet coefficients. The proposed method [3] computed various statistical parameters as Specificity 100%, Sensitivity 83.6%, and accuracy 91.8% for five patients. Hunyadi et al [4] proposed an automated seizure detection technique using CHB-MIT EEG data sets. In this proposed method 80% of data was used for training for 23 numbers of patients. There are 16 numbers of elements are separated in various discrete domain. Sensitivity of 83% is calculated over the whole experimental works. In [5] authors analyzed the CHB-MIT EEG data sets using stacked auto encoders. In this experimental work, the method detected 100% of Sensitivity, considering 6 numbers of patients. In [6], authors implemented a seizure identification technique for extracting various discrete domain features, where 25% of data considered as the training data for 21 numbers of patients. It was experimented on 18 numbers of channels. The proposed method computed the various statistical parameters like Specificity of 94.71% and Sensitivity of 89.01%.

Fiirbas et al. [7] proposed an automated seizure identification method where episcan is used. In this 23 numbers of patient's EEG data are utilized for experimental works. The Sensitivity of 67% is achieved. Samiee et al. [8] in 2015 extracted multivariate textural features from grey level co-occurrence matrix for epileptic Seizure detection. This method [8] used 23 patients, 23 channels and 25% of data for training to complete the whole experimental works. The proposed method achieved 97.74% of Specificity and 70.19% of Sensitivity. In [9] Zabihi et al. proposed an epileptic seizure identification method where seven numbers of features were extracted using 23 numbers of patients and 23 numbers of channels. In this proposed work, 25% and 50% of data are used for training purpose. The calculated results in form of avg. Specificity, Sensitivity and Accuracy rates are 93.21%, 88.27% and 93.11% respectively for 25% training data and for 50% training data, the calculated results for avg. Specificity, Sensitivity and Accuracy rates are 94.80%, 89.10%, and 94.69% respectively.

A.Chb-Mit-Eeg Data Set

In this work, long data sets of EEG signals are recorded for a long duration of time which has taken from PhysioNet [10] CHB-MIT Electroencephalogram dataset, mentioned in [11]. The Electroencephalogram signals are recorded from twenty-three numbers of affected people including both male and female. The age of affected male persons lies in the range of three to twenty-two years whereas the affected female persons are in the range of two to Nineteen years. The experimental analysis is done for individual patients, where minimum (T_{min}) and maximum (T_{max}) time period of seizure events are recorded. T_{min} and T_{max} are different for respective patient, similarly total seizure time and seizure free time are being recorded. The sampling rate for Electroencephalogram signals is 256 Hz and the recorded resolution is 16- bits. To record all the EEG signals twenty three EEG channels are utilized.

II. METHODOLOGY

A. Wavelet Packet Decomposition

All the three datasets (DS1, DS2, and DS3) containing scalp EEG data are demultiplexed at eighth level by WPT, which is the appropriate option for processing of EEG signals compared to Fast Fourier transform and Short-time Fourier transform [12, 13]. R.Dhiman et al, proposed a model to demultiplex signal using WPT [14]. The multi resolution analysis using WPD for a signal g(t) is specified [15, 16]:

$$C_0^0 = g(t) \qquad (1)$$

$$C_i^{q+1} = \sum_k h_0\,(k-2t)C_i^q \qquad (2)$$

$$C_{2i+1}^{q+1} = \sum_k h_1(k-2t)C_i^q \qquad (3)$$

$$i = 0, 1, 2, \ldots\ldots 2^{q-1}$$

Here, C_i^q means the demultiplex coefficient at i^{th} node of qth level, $h_0(n)$ and $h_1(n)$ are orthogonal filters for demultiplexing method. $h_1(n)$ is transfer function of HPF and $h_0(n)$ is transfer function of LPF, which validates the following time domain equation :

$$h_1(n) = (-1)^n h_0(n-1) \qquad (4)$$

B. Improved PSO

In traditional PSO system each particle is identified by its position and velocity in the search area which upgrade them based on its actual value and its neighbor estimated value. In this paper we have proposed an ANFIS based modified training algorithm over as usual use of Particle Swarm Optimisation (PSO) algorithm. The different parameters such as centre, weight, expansion are trained by using swarm optimization algorithm. The main estimated steps of PSO include the basic values of initial position and velocity of each particle and updating position and for a fixed number of generations to get the optimised solution.

In this work, the general PSO is modified in a manner that, initially 'n' number of random particles are created. The particle having best cost would be chosen. In the next stage n number of copies of the chromosomes is generated, then for each chromosome, a random gene would be chosen and shifted to an arbitrary position. If the estimated destination is occupied with another, these two will be interchange their position.

The final result of this MPSO operation as shown in fig.2 is equal to shifting towards best position as in traditional PSO. Among all finalize particles, the best one would be selected and next iteration will be continue till the termination criteria met.

In this present method we have used two types (linear and non linear) of selection strategy for inertia weight . In linear selection w should reduce rapidly,while in non linear w will reduce slowly. Let $w_0$be the initial value of inertia weight $w_1$is the terminared point of linear selection, n_1 is the number of generations for linear selection and n_2 is the number of generation for non linear selection. According to the proposed algorithm for 1 to n_1 number of generations, the inertia weight for MPSO will be calculated as:

$$w_1=w_0-((w_1/n_1)*i) \qquad \text{where } i=1,2,3\ldots\ldots\ldots\ldots n_1 \qquad (10)$$

For n_1 and n_2 number of generations the inertia weight for MPSO will be calculated as

$$w_1=(w_0-w_1)*\exp(((n_1+1)-i)/i) \qquad \text{where } i= g_1\ldots\ldots g_2 \qquad (11)$$

In this work we have taken 220 number of generations. Linear and non linear selection of the inertia weight takes place for about 50% of the maximum number of generations.

C. Classifier used in our work

In this research work, for classification of normal, interictal and ictal EEG signals, fourn number of classifiers are used. They are WPT-IPSO-MLPNN[20], WPT-IPSO-RBFNN [21], WPT-IPSO-ANFIS [22] and WPT-IPSO-ELANFIS [23] is used. There are many choices of dividing the recorded data into training and test [23] sets. In this study, cross validation is considered as k= 10. For statistical parameter evaluation, k-fold technique is used by using training and testing data sets. The average accuracy and other statistical parameters are experimentally computed after the process repeated for k-times. MLPNN is Multilayer Perceptron Neural Network in which node of the hidden layer has a neuron that can performs a nonlinear activation features. MLPNN has a determined planning for taking input and output information to give a proper design . RBFNN consists of one hidden layer which is usually trains by supervised training algorithm. RBFNN is more suitable for nonstationary data where Gaussian function is used. Adaptive Neural network structure is implemented in ANFIS network. In our work, ANFIS classifier is used to detect ictal and pre-ictal EEG signals. Extreme learning ANFIS is a simple learning technique which bypass the learning complexicity and also avoids the randomness of the outputs inherent in ELM networks using fuzzy membership functions.

In this method a modified version of particle swarm optimization is used to train the 9- Rule ANFIS Network for proper classification of normal EEG Signal and IE affected EEG Signal of child of woman having epilepsy . Also to classify between normal EEG signal and IPE affected EEG signal of below 8 years child.

The EEG data sets are composed of non-epileptic EEG Signal as threshold level and recorded IE signal from six women having epilepsy.Also recorded IPE are taken from six children having epilepsy which is genetically transfered from mother to their respective child. Samples correctly classified and misclassified are labeled, respectively, as True Positive (TP) and False Negative (FN). On the other hand, samples of another class can be classified as True Negative (TN) or false positive (FP).

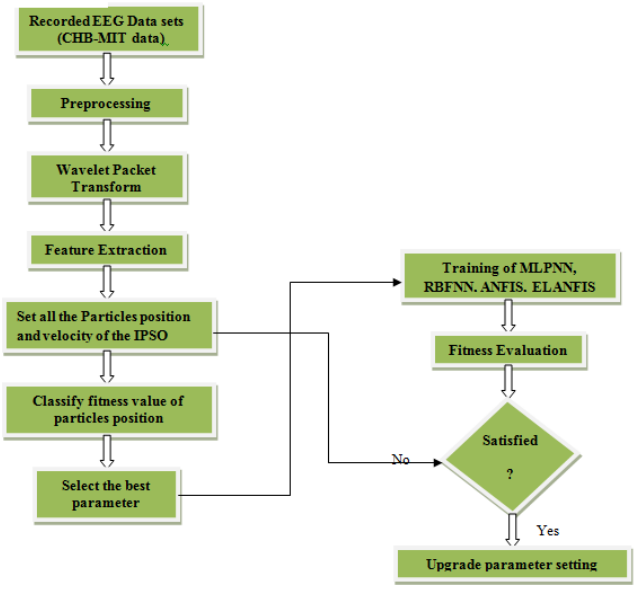

Fig.1. Block Diagram of the proposed method

III. PERFORMANCE MATRIX

This research work evaluates the performance of the proposed methods using various statistical parameters [24] Accuracy (Ac), Specificity (Sp), Sensitivity (Se),G-mean(GM), Positive Predictive(PPV), Negative predictive value (NPV), Area Under Curve(AUC) and also execution time are considered for the validation of the proposed method which are specified from Equation no (11) to Equation no (16).

$$A_c = \frac{TP}{TP + TN + FP + FN} \quad (11)$$

$$S_p = \frac{TN}{TN + FP} \quad (12)$$

$$S_e = \frac{TP}{TP + FN} \quad (13)$$

$$G_M = \sqrt{S_e \times S_p} \quad (14)$$

$$PPV = \frac{TP}{TP + FP} \quad (15)$$

Where, NPV = $\frac{TN}{TN + FP}$ (16)

IV. RESULTS AND DISCUSSION

The block diagram of the proposed method is shown in "Fig .1". Six numbers of Statistical parameters are calculated for the performance evaluation. In the proposed method, various classifiers are used like WPT-IPSO-MLPNN, WPT-IPSO-RBFNN, WPT-IPSO-ANFIS, and WPT-IPSO-ELANFIS for the evaluation of statistical parameters. It is experimented on 23 numbers of patients. Table-I shows that WPT-IPSO-ELAFIS classifier outperforms in all aspects of performance evaluation for every set of experimental works. Table-II to Table-V shows the evaluated performance parameters using WPT-IPSO-MLPNN, WPT-IPSO-RBFNN, WPT-IPSO-ANFIS, and WPT-IPSO-ELANFIS classifiers in which Accuracy, Specificity, Sensitivity, G-mean, PPV & NPV are experimentally calculated which are shown in their respective table. The performance evaluation of the proposed method is also compared with the existing methods for the seizure detection which is shown in Table-VI.

Table-I: Observation of Statistical parameters in proposed methods

Statistical Parameters (%)	WPT-IPSO-MLPNN	WPT-IPSO-RBFNN	WPT-IPSO-ANFIS	WPT-IPSO-ELANFIS
Accuracy	98.43	98.05	97.83	98.98
Specificity	98.88	99.12	99.02	99.3
Sensitivity	94.15	94.61	93.81	96.63
G-mean	96.45	96.83	96.35	97.93
PPV	99.33	98.06	97.76	99.17
NPV	99.33	98.06	97.76	99.41

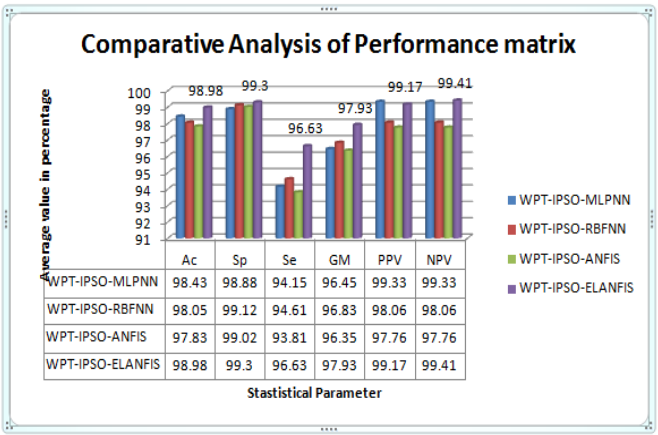

Fig.2. Comparative analysis of performance matrix using various classifiers

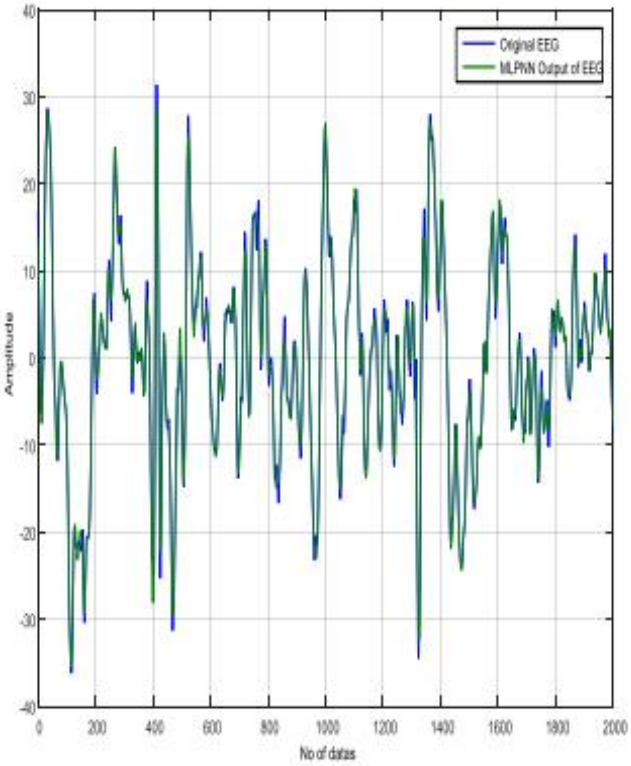

Fig.3. Experimental output of WPT-IPSO-MLPNN Classifier

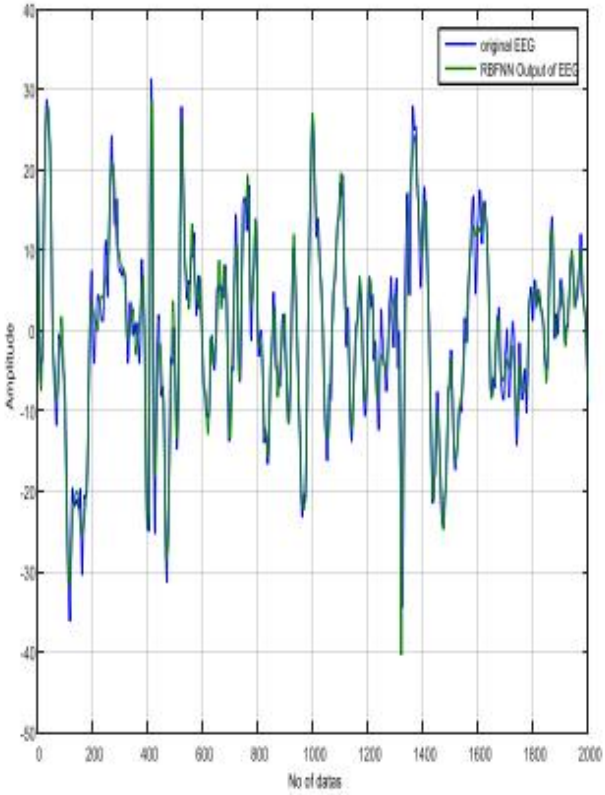

Fig. 4. Experimental output of WPT-IPSO-RBFNN Classifier

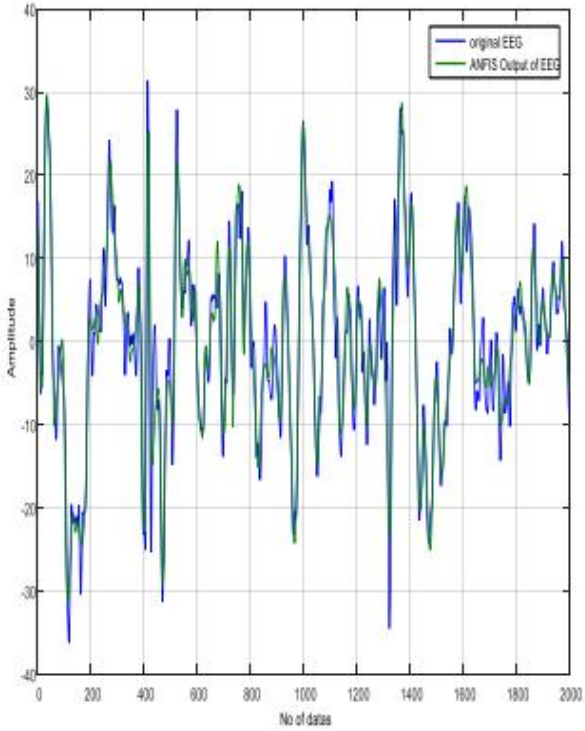

Fig.5. Experimental output of WPT-IPSO-MLPNN Classifier

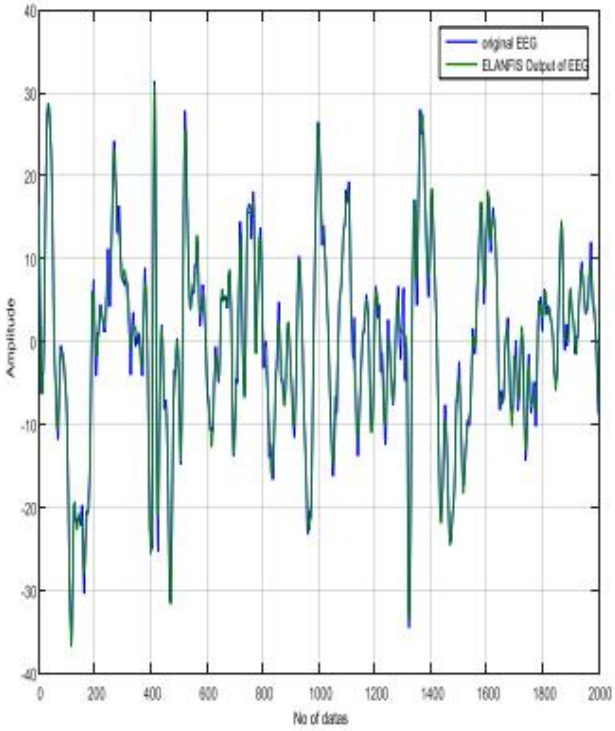

Fig.6. Experimental output of WPT-IPSO-MLPNN classifier

Table-II: Evaluated performance parameters using WPT-IPSO-MLPNN classifier

METHOD	WPT-IPSO-MLPNN Classifier									
FEATURE SETS	***TP***	***FN***	***TN***	***FP***	S_P *(%)*	S_e *(%)*	A_C *(%)*	G_M *(%)*	***PPV (%)***	***NPV (%)***
F_1 (Minimum Amplitude)	337	8	2835	28	99.0	97.7	98.9	98.3	99.7	99.7
F_2 (Mean)	448	14	3140	8	99.7	97.0	99.4	98.3	99.6	99.6
F_3 (Skewness)	559	24	3260	89	97.3	95.9	97.1	96.6	99.3	99.3
F_4 (Kurtosis)	532	17	2780	35	98.8	96.9	98.5	97.8	99.4	99.4
F_5 (Sample entry)	422	19	2616	15	99.4	95.7	98.9	97.5	99.3	99.3
F_6 (Application Entry)	212	20	2790	4	99.9	91.4	99.2	95.5	99.3	99.3
F_7 (Fuzzy Entry)	221	22	2500	15	99.4	90.9	98.7	95.1	99.1	99.1
F_8 (Hurst Exponent)	171	24	2500	64	97.5	87.7	96.8	92.5	99.0	99.0
Average (%)					98.88	94.15	98.43	96.45	99.33	99.33

Table-III: Evaluated performance parameters using WPT-IPSO-RBFNN classifier

METHOD	WPT-IPSO-RBFNN Classifier									
FEATURE SETS	***TP***	***FN***	***TN***	***FP***	S_P *(%)*	S_e *(%)*	A_C *(%)*	G_M *(%)*	***PPV (%)***	***NPV (%)***
F_1 (Minimum Amplitude)	460	15	3500	25	99.3	96.8	99.0	98.1	99.6	99.6
F_2 (Mean)	230	10	3750	20	99.5	95.8	99.3	97.6	99.7	99.7
F_3 (Skewness)	456	20	3490	15	99.6	95.8	99.1	97.7	99.4	99.4
F_4 (Kurtosis)	585	13	3390	10	99.7	97.8	99.4	98.8	99.6	99.6
F_5 (Sample entry)	745	45	800	16	98.0	94.3	96.2	96.2	94.7	94.7
F_6 (Application Entry)	570	16	3400	14	99.6	97.3	99.3	98.4	99.5	99.5
F_7 (Fuzzy Entry)	279	56	700	15	97.9	83.3	93.2	90.3	92.6	92.6
F_8 (Hurst Exponent)	455	20	3200	20	99.4	95.8	98.9	97.6	99.4	99.4
Average (%)					99.12	94.61	98.05	96.83	98.06	98.06

Table-IV: Evaluated performance parameters using WPT-IPSO-ANFIS classifier

METHOD	WPT-IPSO-ANFIS Classifier									
FEATURE SETS	***TP***	***FN***	***TN***	***FP***	S_P *(%)*	S_e *(%)*	A_C *(%)*	G_M *(%)*	***PPV (%)***	***NPV (%)***
F_1 (Minimum Amplitude)	100	15	1000	21	97.9	87.0	96.8	92.3	98.5	98.5
F_2 (Mean)	220	10	3750	12	99.7	95.7	99.4	97.6	99.7	99.7
F_3 (Skewness)	475	20	3490	15	99.6	96.0	99.1	97.7	99.4	99.4
F_4 (Kurtosis)	585	67	900	10	98.9	89.7	95.1	94.2	93.1	93.1
F_5 (Sample entry)	560	20	3200	17	99.5	96.6	99.0	98.0	99.4	99.4
F_6 (Application Entry)	570	16	3400	14	99.6	97.3	99.3	98.4	99.5	99.5
F_7 (Fuzzy Entry)	548	45	600	15	97.6	92.4	95.0	95,0	93.0	93.0
F_8 (Hurst Exponent)	455	20	3700	23	99.4	95.8	99.0	97.6	99.5	99.5
Average (%)					99.02	93.81	97.83	96.35	97.76	97.76

Table-V: Evaluated performance parameters using WPT-IPSO-ELAFIS classifier

METHOD	WPT-IPSO-ELANFIS Classifier									
FEATURE SETS	***TP***	***FN***	***TN***	***FP***	S_P *(%)*	S_e *(%)*	A_C *(%)*	G_M *(%)*	***PPV (%)***	***NPV (%)***
F_1 (Minimum Amplitude)	430	15	3500	25	99.3	96.6	99.0	98.0	99.6	99.6
F_2 (Mean)	220	10	2000	20	99.0	95.7	98.7	97.3	97.6	99.5
F_3 (Skewness)	475	20	3490	15	99.6	96.0	99.1	97.7	99.4	99.4
F_4 (Kurtosis)	345	10	3390	10	99.7	97.2	99.5	98.4	99.7	99.7
F_5 (Sample entry)	745	15	1000	16	98.4	98.0	98.3	98.2	98.5	98.5
F_6 (Application Entry)	570	10	3400	21	99.4	98.3	99.2	98.8	99.7	99.7
F_7 (Fuzzy Entry)	380	18	3556	15	99.6	95.5	99.2	97.5	99.5	99.5
F_8 (Hurst Exponent)	455	20	3200	20	99.4	95.8	98.9	97.6	99.4	99.4
Average (%)					99.3	96.63	98.98	97.93	99.17	99.41

Table-VI: Comparative Analysis of existing methods and the proposed method

Reference No.	Method	Ac (%)	Sp (%)	Se (%)	GM (%)	PVV (%)
2	Statistical parameters calculated from EEG signal considering the wavelet coefficients	80.16	Not recorded	Not recorded	Not recorded	Not recorded
3	Relative values of energy & normalized coefficients of variations calculated from Wavelet coefficients	91.8	100	83.6	Not recorded	Not recorded
4	Sixteen numbers of features, extracted in time and frequency domain	Not recorded	Not recorded	83	Not recorded	Not recorded
5	Unsupervised feature learning using Stacked auto encoders	Not recorded	Not recorded	100	Not recorded	Not recorded
6	Features were extracted in time and frequency domain	Not recorded	94.71	89.01	Not recorded	Not recorded
7	Automatic method for Seizure detection using Episcan	Not recorded	Not recorded	67	Not recorded	Not recorded
8	Multivariate textural features were extracted from grey level co-occurrence matrix for epileptic Seizure detection	Not recorded	97.74	70.19	Not recorded	Not recorded
9	An epileptic seizure detection method in which seven numbers of features were extracted (considering 25% training data)	93.11	93.21	88.27	Not recorded	Not recorded
9	An epileptic seizure detection method in which seven numbers of features were extracted (considering 50% training data)	94.69	94.80	89.10	Not recorded	Not recorded
Proposed method	**Eight numbers of features are extracted (WPT-IPSO-MLPNN/WPT-IPSO-RBFNN/WPT-IPSO-ANFIS/WPT-IPSO-ELANFIS)**	**98.43/98.05/97.83/98.98**	**98.88/99.12/99.02/99.3**	**94.15/94.61/93.81/96.63**	**96.45/96.83/96.35/97.93**	**99.33/98.06/97.76/99.17**

V. CONCLUSION

In our research work, an unprecedented Seizure detection algorithm has been proposed for the analysis of multivariate non-stationary EEG signals. All the three datasets (DS1, DS2, and DS3) containing scalp EEG data are first of all decomposed by Wavelet Packet Transform (WPT). Then, Correlation-based Feature Selection method is used for the selection of the features. Finally, all the features are inputted to different rule based Support Vector Machines like WPT-IPSO-MLPNN, WPT-IPSO-RBFNN, WPT-IPSO-ANFIS, and WPT-IPSO-ELANFIS for the evaluation of statistical parameters. In our work, it is examined that, WPT-IPSO-ELANFIS is the best one in every aspects compared to other classifiers. The results in terms of Accuracy, Specificity, Sensitivity, G-mean, PPV & NPV are 98.98%, 99.3%, 96.63%, 97.93%, 99.17%, 99.41% respectively for WPT-IPSO-ELANFIS. The proposed method will be experimented on short data of EEG signal in future.

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