Tunable Quantum Wavelet Transform and Improved PSO Based Novel Evolutionary Extreme Learning Machine for Epilepsy Detection

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Abstract — In our present work, EEG signals of various classes are broken down in Tunable Quantum Wavelet Transform (TQWT) system. The TQWT decays the EEG signals into sub-groups and arranged them into different descending order of frequencies. The nonlinearity of the EEG signals is evaluated by processing from the acquired features, which is additionally utilized as an element for ordering the typical classes of EEG signals. In this work, EEG signals are arranged in a solitary Random forest (RF) classification issues. In the first place classification is done in seizure classes, and the other one is the typical, seizure free classes. Features got from the EEG signal of these classes are feeded to the contribution of arbitrary Random Forest (RF), classifier prepared with improved PSO (IPSO). For seizure free and seizure classes, we accomplished 99.5581% precision, 98.5261% of Sensitivity and 99.6169% of Specificity and 99.0674% of Gmean esteem with RF classifier and TQWT feature extractor.

Keywords — **EEG Signal, Epilepsy, TQWT, IPSO, Random Forest classifier.**

I. INTRODUCTION

The epilepsy is a typical issue of sensory system which influences nature of patient's life [1]. Around the world 65 million individuals are influenced from the epilepsy [2]. Event of the epilepsy is around 50 for each 100,000 populace every year in created nations. The rate of event is higher in low and middle income nations [2]. Electroencephalogram (EEG) can be utilized to distinguish epilepsy. The master specialists and neurologists investigate these signs to evaluate the conditions of the cerebrum, which might be a tedious procedure. The EEG based PC helped methods are discovered extremely viable in diagnosing the epilepsy [2, 3]. Besides, EEG signal processing methods, for example, [4] are useful to spare the memory necessity of PC based indicative frameworks. In this manner, to build up a computerized framework for epilepsy analysis is a territory of distinct fascination for the analysts. Numerous time-area based systems, for example, direct forecast blunder vitality [5] and the fractional linear prediction (FLP) strategy [6] are utilized to recognize epileptic seizures utilizing EEG signals. Time-area and recurrence space highlights are used with Artificial Neural Network (ANN) to identify the epileptic seizure in [7]. In [3], chief part examination is utilized with upgraded cosine outspread premise work neural system to distinguish epileptic seizures. A recently created time-recurrence portrayal technique utilizing eigenvalue deterioration is connected for EEG signals [8]. Experimental mode distribution (EMD) method is effectively utilized for the investigation of EEG signals. This procedure decays the EEG signals into different sufficiency and recurrence regulated signs named as natural mode capacities (IMFs). Mean recurrence registered from IMFs of EEG signals indicated great separation capacity between seizure free and ictal EEG classes [9]. In addition, interquartile scope of Euclidian separations and 95% certainty circle territory are registered from stage space portrayal of IMFs, and indicated great execution in grouping the epileptic seizures [10]. In [11], histogram based highlights are processed from time-recurrence pictures, and used to isolate the EEG signs of seizure class. These pictures are the time– recurrence portrayal of EEG signals acquired utilizing Hilbert-Huang change. EMD and second request distinction plot based approach is investigated for seizure EEG signal order [12]. Additionally, direct, and nonlinear highlights are utilized to break down EEG signals [13]. They found that nonlinear highlights are more appropriate for catching the elements of EEG signals [13]. In writing, the epileptic EEG signals are likewise examined utilizing Discrete Wavelet Transform (DWT) based component extraction techniques which are discovered helpful in the examination of epileptic EEG signals [14, 15]. The Tunable-Quantum Wavelet Transform (TQWT) is connected for dissecting the central and non-central EEG signals [16].Figure 1 shows the block diagram of the proposed model.

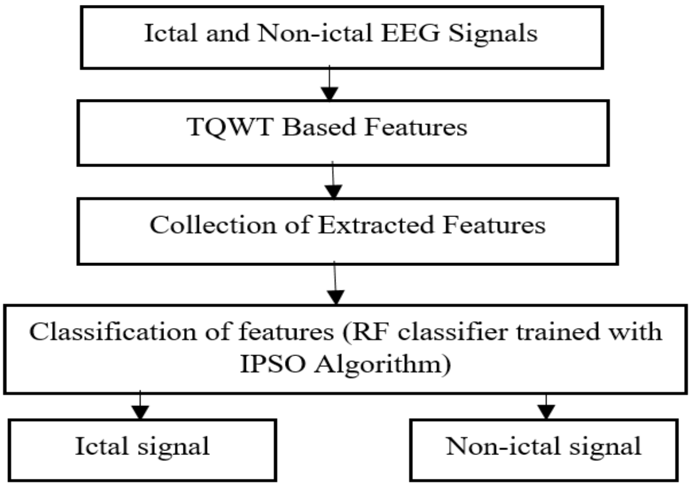

Fig:-1 block diagram of proposed model

In this work, our point is to build up a computerized network for ID of seizure and seizure free EEG signals utilizing lesser signal length in view of highlights removed in TQWT space. The execution of the extricated highlights are assessed utilizing different classifiers. The rest some portion of the paper is sorted out as takes after: In the second area, informational collection, TQWT, and separated element are given. Order strategies are portrayed in third segment. Gotten results and talk are given in the fourth and fifth areas, separately.

II. MATERIALS AND METHODS PAGE LAYOUT

Dataset For this investigation, we have utilized freely accessible EEG dataset as depicted in [17]. The chronicles of EEG signals for both solid and epileptic subjects are accessible in this dataset. The EEG signals are isolated into five subsets to be specific, Z, O, N, F, and S. Every subset contains 100 single-channel EEG signs of length 23.6 s. The EEG signs of subsets Z and O are procured from five solid subjects utilizing standard cathode position plot [17]. These are the surface EEG accounts with eyes open and shut, individually. The subsets F and N comprise the EEG signs of without seizure interims from five patients. These signs are recorded in the epileptogenic zone for F subset and from the hippocampal arrangement of the contrary side of the equator of the cerebrum for N subset. The fifth subset S incorporates the EEG signs of seizure action and taken from all the chronicle locales which demonstrated the ictal movement. The EEG signs of subsets N, F, and S are recorded utilizing profundity terminals intra cranially. The inspecting rate of each recorded EEG signal is 173.61 Hz. The detail depiction of the dataset is given in [17].

A. Feature Extraction Method

Feature are extracted from TQWT. The TQWT is a signal extraction procedure which is broadly utilized as a part of the investigation of biomedical signs [18, 19] It is a reasonable system for breaking down the homeless people and oscillatory segments introduce in the signal. It comprises two movable parameters Quality-factor (Q) and repetition (r) [20]. Higher estimations of Q are reasonable to catch the motions of the signal. In any case, bring down qualities are reasonable to extricate the transient idea of the signs. By changing the estimations of Q and r, time and recurrence determination can be balanced [20]. The TQWT technique can be actualized utilizing two channel bank iteratively [20].

B. Random forest classifier

The order utilizing the Random Function (RF) classifier [21] depends on the aggregate choices of various arrangement trees. To choose the Final result, yield choice of the class made by each tree is considered with a weight. In this calculation, the nth tree is allocated with a stochastic vector δn. The new vector δn has produced autonomously from the past one, and has an indistinguishable dispersion from of the past irregular vectors. From that point, a choice tree is developed based on the preparation input information x and δn, and a tree classifier H(x, δn) is gotten. At long last, the class label is given, in view of the margin function (MG).

C. Evaluation Criteria

STATISTICAL TEST

The classification performance of the classifiers is tested with three parameters namely, accuracy, sensitivity and specificity which are given as follows [22].

$$\text{Sensitivity (SEN)} = \frac{TP}{TP+FN} \times 100 \tag{1}$$

$$\text{Specificity (SPE)} = \frac{TN}{TN+FP} \times 100 \tag{2}$$

$$\text{Accuracy (ACC)} = \frac{TN+TP}{TN+TP+FN+FP} \times 100 \tag{3}$$

$$\mathbf{Gmean} = \sqrt{\mathbf{Sensitivity} * \mathbf{Specificity}} \tag{4}$$

In the above calculations values of TP, FN, TN, and FP are represented the total number of different samples such as true positive, false negative, true negative, and false positive, respectively.

D. Improved Particle Swarm Optimization (IPSO)

(ABC) is a swarm based algorithm very similar to PSO. In any case, it reproduces the scrounging practices of honey bees. For this reason, it utilizes utilized honey bees (in charge of conveying sustenance to the bee colony and for doing smooth movement), passed by honey and detective honey bees (in charge of arbitrary nourishment look). In ABC, utilized honey bee number is equivalent to nourishment source and to spectator honey bees. In addition, number of honey bees in settlement is equivalent to four fold of utilized honey bees number. The utilized honey bee, whose sustenance information source closes, turns into a detective honey bee.

It’s clearly seen that PSO methodology is a lot of sensible and easier to know than first ABC algorithm. In each techniques, updating of particles is finished within the same principle, however via totally different approaches. For this purpose, PSO uses position and velocity operators whereas first algorithm uses utilized bee and looker-on bee phases. However, first method controls the useless particles that couldn’t improve its fitness on a user outlined iteration range referred to as ‘limit’. Also, first ABC makes this method once update a part. So, it’s seen that a demand of limit is inevitable for PSO. Because, it hasn’t got any management parameter reproducing the ineffective particles. First principle keeps in check its particles with scout bees. By adding the scout bee section to PSO, IPSO is obtained. In IPSO, all processes are constant with PSO. Following paragraph shows the Pseudocode for IPSO rule.

Introduce all particles inside the client characterized limits (The primary best position (Pbest) values are equivalent to position of particles)

- Define an utmost incentive inside the range [1, (most extreme cycle number-1)]
  While (emphasis number < most extreme cycle number)
- Calculate wellness as per cost work for all particles

- Update best position esteems as indicated by wellness esteems for all particles
- Choose the best Pbest vector as being Gbest (the vector accomplished to least cost)
- Calculate new positions as indicated by following conditions for all particles

$$Vi(t+1)=\omega Vi(t)+c1r1(Xpbest(i)(t)-Xi(t))+c2r2(Xgbest(t)-Xi(t)) \quad (5)$$

$$Xi(t+1)= Xi(t)+Vi(t+1) \quad (6)$$

-If a variable inertia weight is used, change it in accordance with the used rule

III. RESULT ANALYSIS

In our proposed work we have taken the seizure and seizure free signals of male and female having ages between 25-55 years. The TQWT decomposed the PKU affected signal into upto 6th level of decompositions with different frequency components. The parameters are updated with a suitable input values. Which are highly necessary for better performance of the RF network. IPSO algorithm is used as a trainer to the RF network. Table 1. Shows the statistical performance result (SEN, SPE, ACC, and Gmean of the proposed method, which shows that RF classifier trained with an improved PSO outperforms in all respects. Table 1. Shows the calculated statistical parameters on the basis of true negative (TN), true positive (TP), false negative (FN), false positive (FP). The authors are tried as their best to analyse the sensitivity, specificity, accuracy and Gmean. Table 2 shows the comparative analysis of the existing approach with the observed values of the statistical parameters. Table 3. Shows the clinical observation table. Fig:-2. shows Comparison plot between the original EEG and TQWT-IPSO-RF output data of EEG signal,figure 3 shows the pillar diagram of our different performance result. Figure 4 shows the ROC curve based of our proposed method. Calculated average values of the different performance results are 99.5581% precision, 98.5261% of Sensitivity and 99.6169% of Specificity and 99.0674% of Gmean esteem with RF classifier.

Sl no	TP	FN	TN	FP	ACC	SEN	SPE	Gmean
1	9481	42	18221	182	99.19788011	99.55896251	99.01103081	99.28461867
2	6480	72	19380	142	99.17925903	98.9010989	99.27261551	99.08668309
3	2680	6	32944	61	99.8122776	99.77661951	99.81517952	99.79589765
4	7345	16	11246	39	99.70503057	99.78263823	99.65440851	99.71850276
5	3791	41	51211	37	99.8583878	98.93006263	99.92780206	99.42768084
6	1413	48	25277	78	99.53013126	96.71457906	99.69236837	98.19218626
7	898	42	22388	62	99.55536554	95.53191489	99.72383073	97.60537132
8	5220	131	41548	141	99.42176871	97.55185947	99.66178129	98.60117688
9	1707	4	11320	33	99.71677893	99.76621859	99.70932793	99.7377692
10	2445	31	21720	65	99.6043032	98.74798061	99.70162956	99.22365939
Average values					99.5581	98.5261	99.6169	99.0674

Table:-1. Calculated values of the different statistical parameters.

REFERENCE	METHODS	PERFORMANCE ANALYSIS (%)
[23]	SNN	ACCURACY: 92.5
[24]	GMM	SENSITIVITY: 92.2 SPECIFICITYC: 100
[25]	SVM+PSD Estimation	ACCURACY: 93.3 SENSITIVITY: 98.3 SPECIFICITYC: 96.7
[26]	SVM+RQA	ACCURACY: 95.6 SENSITIVITY: 98.9 SPECIFICITYC: 97.8
[27]	Fuzzy sugeno, WPT	ACCURACY: 96.7 SENSITIVITY: 95 SPECIFICITYC: 99
[28]	EMD, □HT, C4.5 decision tree	ACCURACY: 95.3 SENSITIVITY: 98 SPECIFICITYC: 97
[29]	Random forest , EMD,	ACCURACY: 99.4 SENSITIVITY: 97.9 SPECIFICITYC: 99.5

PROPOSED WORK[PW]	**RF,TQWT, and IPSO**	**ACCURACY: 99.87** **SENSITIVITY: 100** **SPECIFICITY: 98.71**

Table:-2 comparison analysis of the different optimized values (ACCURACY, SENSITIVITY, and SPECIFICITY) of the proposed method with existing methods.

PI(Patient ID)	Age/Gender	No of seizure events/Time in sec	No. of Channels	Total Seizure time(sec.)	Total Seizure free time(sec.)	Seizure origin
1	29/F	4(15-34)	Chb14	629	29823	Right frontal lobe and central region
2	25/M	3(63-146)	Chb15	909	27258	Left temporal lobe
3	47/F	6(38-82)	Chb16	289	14694	Frontal lobe
4	52/F	8(22-89)	Chb17	437	13732	Right frontal lobe and temporal lobe
5	34/F	4(21-189)	Chb18	249	10480	Right frontal lobe
6	35/F	4(8-17)	Chb19	741	11823	Right central origin
7	46/F	3(9-91)	Chb20	439	14998	Right frontal lobe and central region
8	53/F	12(52-76)	Chb21	1201	17428	Left front and middle temporal lobe
9	39/F	17(32-61)	Chb22	388	10342	Left front and middle temporal lobe
10	36/F	13(7-25)	Chb23	572	14444	Left temporal lobe

Table:-3. Clinical observation

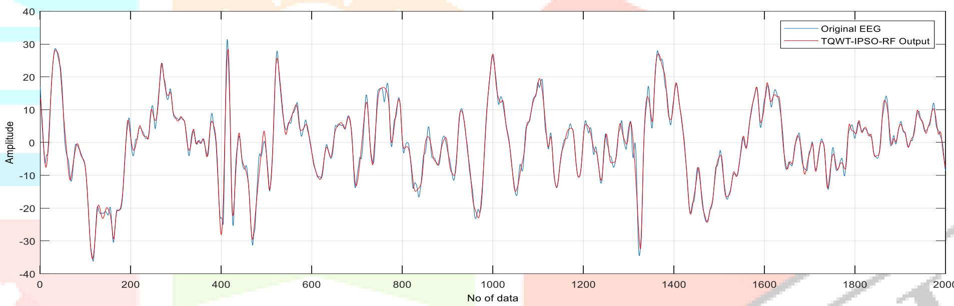

Fig:-2. Comparison plot between the original EEG and TQWT-IPSO-RF output data of EEG signal

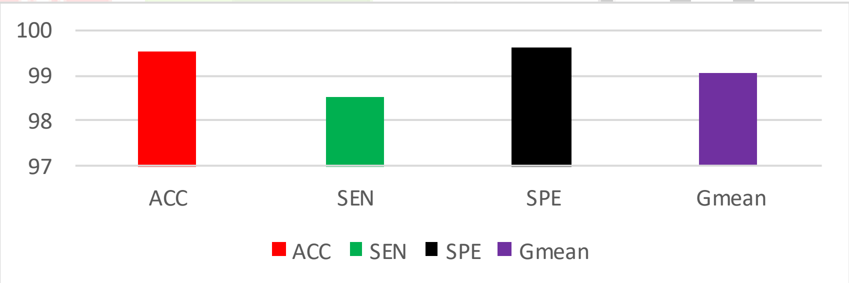

Fig:-3. Bar chart diagram of the different observed values of statistical parameters.

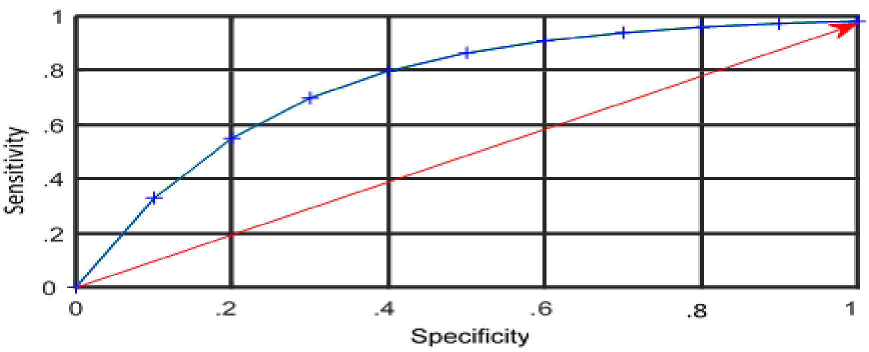

Fig:-4. ROC Curve of our proposed method

IV. CONCLUSIONS

From authors information first time for practical analysis, this work actualizes with enhanced method for the recognition and legitimate grouping of unique EEG (both seizure and non-seizure). This strategy utilized RF arrange as a classifier. TQWT utilized as a pre-processor to expel the instrumental and biological factors. Proposed altered calculations (IPSO) is utilized to advance and refreshing the parameters to prepare and test the RF organize for appropriate conclusion. From measurable tests and examination with existing strategies we have inferred that our proposed technique gives better execution in all regard. The out execution of the proposed technique is appeared in the ROC curve, comparison diagram and piller diagram with a higher accuracy as shown figure. Because of change of measurable parameters (high affectability, specificity and precision) when contrasted with the current approach said in table1, it might be utilized for constant arrangement of the seizure influenced EEG signal and unique EEG motion in practical applications for efficient clinical treatment.

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