A real-time automated epileptic seizure detection model for phenylketonuria patients using ANFIS, DWT, ST, CT and EGA

Sumant Kumar Mohapatra* and
Srikanta Patnaik

Department of Computer Science and Engineering,
S'O'A (Deemed to be University),
Odisha, India
Email: sumsusmeera@gmail.com
Email: srikantapatnaik@soa.ac.in
*Corresponding author

Abstract: One of the most ARSG diseases is a phenylketonuria (PKU). The patient suffered from the deficiency of blood circulation across brain which shows small epileptic seizure in EEG signal. In this work, three feature extraction methods (discrete wavelet transform, shearlet transform and contourlet transform) have been used to classify epileptic seizure EEG (PKU-EEG) and raw EEG signals (non-epileptic seizure EEG). The classification between PKU-EEG and raw EEG signals are performed using nine-rule adaptive neuro-fuzzy inference system (ANFIS) trained with a new enhanced genetic algorithm (EGA). The CT-ANFIS-EGA method outperforms than above methods for the classification of normal EEG and PKU-EEG signals. The proposed method has the accuracy, sensitivity and specificity of 99.82%, 99.88% and 99.93% respectively using real datasets. This study suggests that the proposed work could be effective for clinical classification of epileptic seizure by PKU in the children from their early childhood ages.

Keywords: PKU-EEG signal; epilepsy; single gene; EEG signal; adaptive neuro-fuzzy inference system; ANFIS; discrete wavelet transform; DWT; shearlet transform; ST; contourlet transform; CT; enhanced genetic algorithm; EGA.

Reference to this paper should be made as follows: Mohapatra, S.K. and Patnaik, S. (2022) 'A real-time automated epileptic seizure detection model for phenylketonuria patients using ANFIS, DWT, ST, CT and EGA', *Int. J. Telemedicine and Clinical Practices*, Vol. 3, No. 4, pp.302–326.

Biographical notes: Sumant Kumar Mohapatra received his BTech from the ITER, Bhubaneswar, India in 2002 and MTech in Electronics and Instrumentation Engineering from the GIET, BPUT, Odisha in 2011. He is currently working in Trident Academy of Technology, B.P.U.T, Bhubaneswar, Odisha, India as an Assistant Professor and Research Scholar at the S'O'A (Deemed to be University), Bhubaneswar, India. His research interests are in signal and image processing, optical fibre communication and wireless communication and biomedical signal processing.

Srikanta Patnaik is presently serving as a Professor of Computer Science and Engineering at the S'O'A University, Bhubaneswar, India. He holds a Doctor of Philosophy in Engineering from the Jadavpur University, India. He has published more than 80 research papers and articles in international journals and magazines of repute. He has supervised ten research scholars for their PhD. He has completed various funded projects as a principal investigator from various funding agencies of India. He is the Editor-in-Chief of two international journals namely, *International Journal of Information and Communication Technology* and *International Journal of Computational Vision and Robotics*, published from Inderscience Publishing House, UK and also Editor-in-Chief of Springer book series on *Modeling and Optimization in Science and Technology [MOST]*.

1 Introduction

Epilepsy is a central nervous system (neurological) disorder in which brain activity becomes abnormal, causing seizures or periods of unusual behaviour, sensations, and sometimes loss of awareness. 0.6–0.8% of the world's populations are affected by epilepsy (Adelui et al., 2003). Electroencephalogram (EEG) is a valuable measure of the brain's electrical function and generated by the cerebral cortex's nerve cells. In medical research it is found that deficiency of Phenylanine hydroxylase (PAH, Gene 612349) in children creates genomic abnormalities. Due to the above deficiency, phenylketonuria (PKU) developed which is an inherited disorder that increases the levels of a substance called phenylalanine in the blood. Phenylalanine is a building block of proteins, i.e., amino acid obtained through the proper diet. This is also developed due to neurotoxic effect of hyperphenylalaninemia (Zurfluh et al., 2008). Paine (1957) told that due to PKU, the mental retardation arises in untreated patients which lead to develop epilepsy. Therefore, it is very much necessary to classify the normal and epilepsy seizure EEG signals for the proper diagnosis. Many researchers had considered EEG signal as an important tool for analysing the human brain activity for providing relevant information about epileptic process by implementing different feature extraction methods and classifiers to measure the accuracy between normal and epilepsy seizure EEG signals. Patidar and Panigrahi (2017) proposed an advanced feature extraction method from EEG signal based on tunable-Q wavelet transform method for the diagnosis of alcoholism. Nigam and Graupe (2004) proposed a neural network-based model for the detection of epilepsy. They have used a nonlinear preprocessing filtering method for the feature extraction. Kannathal et al. (2005) proposed entropy-based adaptive neuro fuzzy inference system for the detection of epilepsy. Guler et al. (2005) proposed a recurrent neural networks method for EEG signal classification by employing Lyapunov exponents. Many authors have presented their proposed model for EEG signal classification using wavelet-based feature extraction and neural networks with different accuracy value such as accuracy of 94% (Ataee et al., 2006), accuracy of 97% (Jahankhani et al., 2006), accuracy of 95% by implementing mixture of some expert models (Subasi, 2007), accuracy of 97.73% by analysing the signal in time-frequency domain (Tzallas et al., 2007), accuracy of 96.89% (Ubeyli, 2008), accuracy of 98.27% by implementing multiwavelet entropy and permutation entropy features (Guo et al., 2010) etc. Nicolaou and Georgiou (2012) proposed an advanced algorithm for supervised learning for EEG data classification and regression analysis based on support vector machine. Alam and Bhuiyan (2013) was able to detect the epileptic seizure using higher order statistics in the EMD domain based on dual tree complex wavelets to achieve better performance in terms of accuracy. Das et al. (2014) proposed an automated statistical method for the detection of seizure and epilepsy in the dual tree complex wavelet transform domain. The epileptic seizure in EEG signal was also detected by using DWT-based artificial neural network system (Kumar et al., 2014). Das et al. (2016) proposed a model for the classification and seizure detection of EEG signals using normal inverse Gaussian parameters in the dual tree complex wavelet transform domain. Better accuracy was achieved by implementing advanced classifier using the K-mean clustering and a multilayer perceptron neural network model (Orhan et al., 2011). The epileptic seizure can also be detected automatically using wavelet transform and support vector machine method in long-term intracranial EEG signal (Liu et al., 2014). Ling et al. (2009) proposed an artificial neural network model for the classification of EEG signal using relative wavelet energy method. They were able to achieve an accuracy of 95.20%.

Li et al. (2017) proposed a DWT-based EA feature extraction method with NNE to improve the accuracy of classification. To measure the various statistical parameters like sensitivity and specificity of the classified normal and epilepsy seizure EEG signals, scores of authors have presented their model by using different feature extraction methods and classifiers. These methods include Stockwell transform and boosting algorithm for long-term EEG (Yan et al., 2015), differential operator and windowed variance method (Majumdar and Vardhan, 2011), fuzzy rule-based system in intracranial EEG (Aarabi et al., 2009), patient specific seizure detection during pre surgical evaluation (Chua et al., 2011), wavelet transform, phase-space reconstruction and Euclidean distance method (Lee et al., 2014), cross-correlation aided support vector machine method (Chandaka et al., 2009), fractional linear prediction method (Joshi et al., 2014), Kraskov entropy applied on tunable-Q wavelet transform (Patidar and Panigrahi, 2017), robust expert system design for automated detection of epileptic seizures using SVM method (Swami et al., 2014), standard deviation, entropy and general regression neural network (Swami et al., 2016), least square support vector machine method (Pachori and Patidar, 2014) etc. Zabihi et al. (2016) proposed an algorithm for the analysis of high-dimensional phase space through Poincare section to detect the epileptic seizure. Luijtellar et al. (2016) proposed an automated advanced model for seizure detection in EEG signal. They implemented the method where the possibilities for the prediction in genetic absence models can be done. Bhattacharyya et al. (2016) proposed an empirical wavelet-based model for the automatic detection of seizure for the focal EEG signal. Peng et al. (2016) proposed a modified feature selection model. This work investigates how the traditional image classification pipelines can be extended into a deep architecture, inspired by deep neural networks. This deep boosting framework based on layer-by-layer joint feature boosting and dictionary learning. Song et al. (2016) proposed a model for feature extraction and selection in an efficient manner. This work proposes a new Mahalanobis-similarity-based feature extraction method on the basis of Mahalanobis distance and discrete wavelet transformation and for the further improvement in performance, this proposed model designed a fusion feature in the feature-fusion-level. Bandarabadi et al. (2015) proposed a model by applying machine learning methods on a reduced subset of proposed features which can predict seizure onsets with high performance. The proposed algorithm was evaluated on continuous long-term multichannel scalp and invasive recordings (183 seizures, 3,565 hr). The best results demonstrated a sensitivity of 75.8% (66 out of 87 seizures) and a false prediction rate of 0.1 h (–1).

EEG signals contain non-stationary transient events and multiple frequency components that vary over time. Such signal characteristics motivated the use of time-frequency shearlet and contourlet transforms (CTs) (Paulo et al., 2017), which are appropriate to decompose the EEG components at different resolution levels. In contrast to the limited ability of wavelet transforms in decomposing signals only at horizontal, vertical and diagonal direction, shearlet and CTs provide an effective method for overcoming such directional limitations. Therefore, features extracted from the time frequency representation can explore variations in amplitude and frequency components of the EEG signals (such as spikes, slow and sharp waves), which are used to discriminate between epileptic and normal EEG signals.

Many authors as mentioned above in this section have used publicly available datasets such as Bonn University EEG dataset and CHB-MIT EEG datasets. In our work, real-time PKU affected EEG signals which contains seizures are taken into account to compute the statistical analysis, from author's knowledge. This is the first time, this real data from National Institute of Mental Health and Neuro Science (NIMHANS), Bangalore, India is experimented by using an automated epileptic seizure detection model. This paper describes a novel work on epileptic PKU-EEG analysis through different time frequency transform such as discrete wavelet, shearlet and contourlet. Initially the EEG signals are decomposed into frequency bands using each transform. Then, a set of features are extracted from the transform coefficients and used as input to a nine-rule ANFIS classifier trained with an enhanced genetic algorithm (EGA) to get the classified epileptic PKU-EEG and raw or normal EEG signals. To the best of our knowledge this is the first work to use shearlet and CT in addition with nine-rule ANFIS plus EGA to classify above said EEG signals from PKU patients. For this experimental computation, authors have used three well known decomposers (Paulo et al., 2017), ANFIS network and an EGA. Finally, (CT + ANFIS + EGA) method has got the high accuracy, sensitivity and specificity as 99.82%, 99.88% and 99.93% respectively. In future, it will be experimented on publicly available datasets.

2 Materials and methods

2.1 Signal recording

In this study the PKU affected EEG (PKU-EEG) signals are collected from channels on the scalp of the children. This data were collected from PKU on diet patients within the age 5 to 10 years of male and female. Raw EEG signals were taken from 12 healthy children (seven male and five female) in this work six number of PKU patient's data are recorded. The RAW EEG and PKU-EEG signals have been recorded from NIMHANS, Bangalore, India. For recording of the signals, 128 numbers of channels with 173.61 Hz of signal and 12-bit resolution are used.

3 Features extraction methods

3.1 Discrete wavelet transform (DWT)

In this work, DWT is used for feature extraction from recorded EEG signals are used as shown in Figure 1.

General formula for DWT is:

$$v[k] = (v * g)[k] = \sum_{n=-\infty}^{\infty} u[n]g[k-n] \quad (1)$$

For approximation co-efficient formula is:

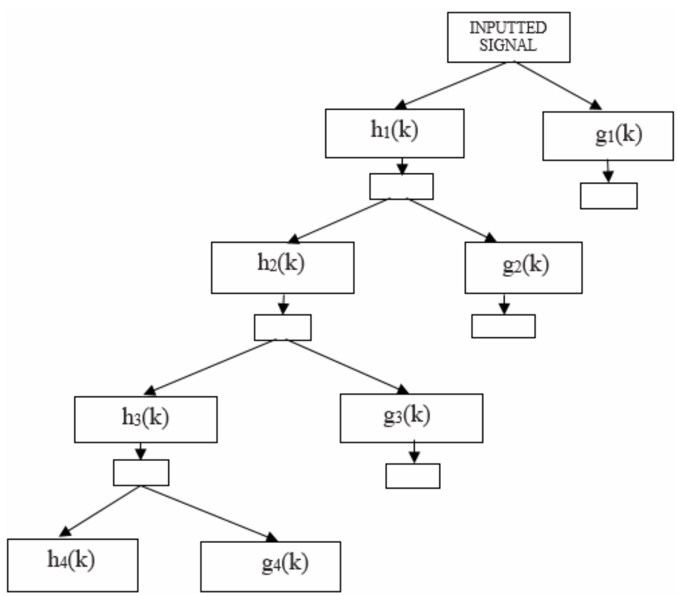
$$v_{low}[k] = \sum_{n=-\infty}^{\infty} u[n]g[2k-n] \quad (2)$$

For detail co-efficient formula is:

$$v_{high}[k] = \sum_{n=-\infty}^{\infty} u[n]h[2k-n] \quad (3)$$

Figure 1 shows the four level decomposition using DWT. The real-time EEG signal is inputted and in first step the signal is decomposed into $h_1(k)$ and $g_1(k)$ and so on to get the $h_4(k)$ and $g_4(k)$.

Figure 1 Four level decomposition using DWT



3.2 Shearlet transforms (STs)

The second type of feature extraction method used in our proposed model is ST (Lim, 2010; Schwartz et al., 2011). The continuous ST of a recorded EEG signal in 2D form is represented by:

$$f \to SH\psi f(a, s, b) = (f, \psi a, s, b) \quad (4)$$

where ψ is a generating function, $a > 0$ is the scale parameter, $s \in R$ is the shear parameter, $b \in R^2$ is the translation parameter, and the analysing elements $\psi_{a,s,b}$ (shearlet basis functions) are given by:

$$\psi_{a,s,b}(x) = a^{-3/4}\psi\left(A^{-1}S^{-1}(x-b)\right) \quad (5)$$

where $A = \begin{bmatrix} a & 0 \\ 0 & \sqrt{a} \end{bmatrix}$ and $S = \begin{bmatrix} 1 & s \\ 0 & 1 \end{bmatrix}$.

The shearlets $\psi_{a,s,b}$ form a collection of well-localised waveforms at various scales a, locations b and orientations (Wang et al., 2014).

3.3 Contourlet transform

The CT (Do and Vetterli, 2005) is an appropriate double filter band decomposition method used in this work. The recorded PKU-EEG and raw EEG signals are decomposed by using this method for feature extraction.

4 Enhanced genetic algorithm

The steps of EGA are elaborated as:

Step 1 The population size, maximum generation size, cross over rate (R_C), mutation rate (R_m) and the increment or decrement rate (improvement rates, R_i) are determined.

Step 2 Generate a current solution (C_s) and temporary solution (T_S).

Step 3 To manage the population in an order, the experiences are created and evaluated individually.

$$e_g = \begin{cases} 1 & s_g < s'_g \\ 0 & s_g = s'_g g = 1, 2 \ldots n \\ -1 & s_g > s'_g \end{cases} \quad (6)$$

where

$$E = \{e_1, e_2 \ldots\ldots e_n\}, S = \{s_1, s_2 \ldots\ldots s_n\}, s' = \{s'_1, s'_2 \ldots\ldots\ldots s'_n\}$$

Step 4 The fitness values are evaluated in an order for each experience.

Step 5 In this step, from the group of experiences in Step 4, select the most valuable and common experience to put the on the top.

Step 6 Randomly select the two chromosomes of two parents with high fitness values.

Step 7 From Step 5 a new offspring is outcome depending upon their crossover rate.

Step 8 A genetic diversity is maintained from new offspring to get mutation rate.

Step 9 From Step 7 and Step 8, a new solution is developed as follows:

$$S'_g = \begin{cases} S_g + R_m \times |S_g|, & e_g = 1 \\ S_g, e_g = 0, & g = 1, \ldots, n \\ S_g - R_m \times |S_g|, & e_g = -1 \end{cases} \tag{7}$$

where

$$E = \{e_1, e_2 \ldots\ldots\ldots e_n\}$$

$$S_g = \{s_1, s_2 \ldots\ldots s_n\}$$

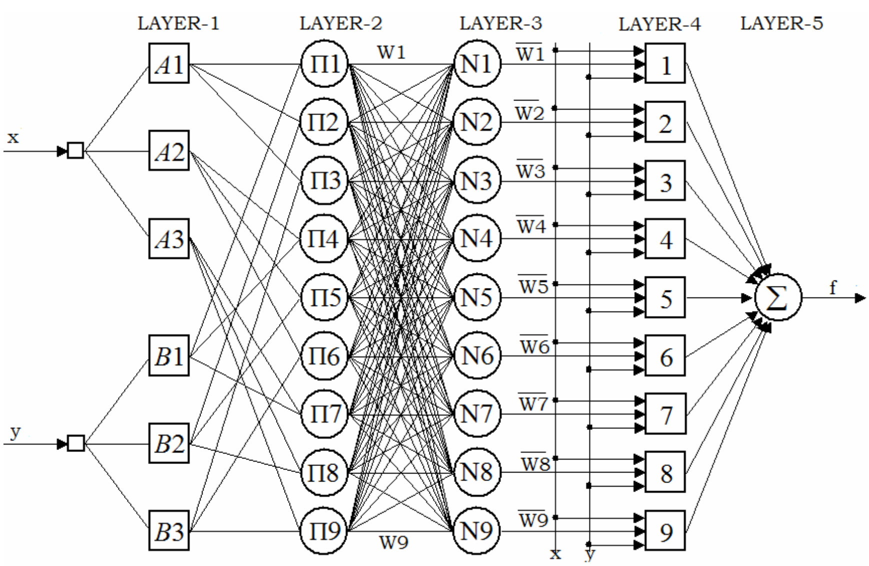
$$S'_g = \{s'_1, s'_2, \ldots\ldots, s'_n\}$$

R_m = mutation rate which determines the probability of the mutation.

For evaluation, if RMSE (C_S) – RMSE (T_S) > 0 condition is optimised from generated solution S_g, then a new experience e_g is generated with fitness value of 1. Therefore the selected two parent's chromosomes fitness values as discussed in Step 5 are increased. Finally a current solution, if the above said condition is not satisfied, the two parent's chromosomes fitness values are decreased.

Step 10 Experimentally, looped the Steps 4 to 9 till stopping criterion is reached to obtain the current solution.

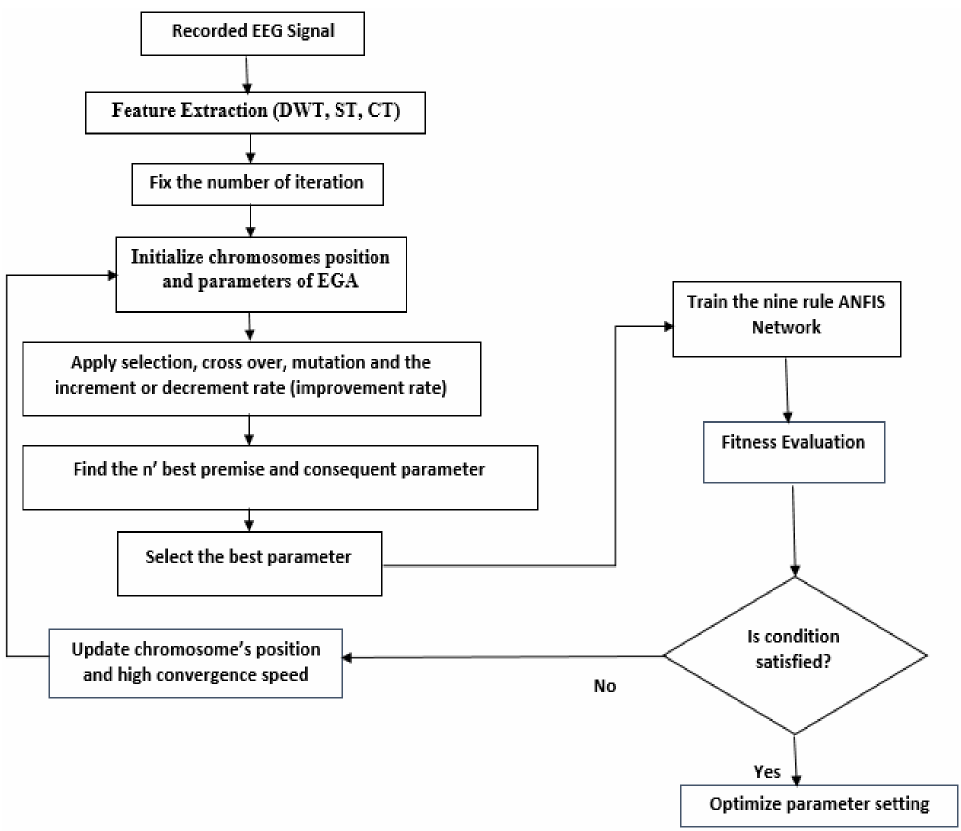
Figure 2 ANFIS network



5 Proposed method

This work describes a method using ANFIS-EGA for detection of healthy and affected EEG signals using time frequency transforms. The ANFIS network and the proposed model are shown in Figure 2 and Figure 3 respectively. In this work, the minimum, maximum and mean absolute values, SD and average power as features are extracted (Subasi and Gursoy, 2010). The recorded EEG signal is inputted to the different transformation methods such as DWT, ST, and CT for extraction of features. The whole dataset is classified into training and testing datasets. The ANFIS classifier's parameters are initialised by GA to get the fitness evaluation.

Figure 3 Block diagram of DWT/CT/ST/ + EGA + ANFIS model



The objective of EGA is to optimise the ANFIS classifier by automatically utilising the best features to discriminate various classes and selecting the best parameters for ANFIS model. The *EGA-ANFIS algorithm* used in this work is as follows:

Step 1 Normalise the input parameters by using minimum and maximum values in the dataset. In this paper equation (7) is used for normalise the input parameters.

Step 2 Initialise all the parameters for the ANFIS.

Step 3 Select the membership function for ANFIS network. For this EEG signal classification, four bell membership functions are used.

Step 4 EGA is introduced to train the optimised parameters as explained in Step 2.

Step 5 Set the fitness values of the parameters by using training dataset.

Step 6 Get the results of the network with optimal parameters by using testing dataset.

Step 7 The EEG signals are tested using trained ANFIS classifier.

6 Performance evaluation

The effectiveness of the method is computed by following statistical parameters.

$$Sensitivity\ (SEN) = \frac{TP}{TP + FN} \times 100 \tag{8}$$

$$Specificity\ (SPE) = \frac{TN}{TN + FP} \times 100 \tag{9}$$

$$Accuracy\ (ACC) = \frac{TN + TP}{TN + TP + FN + FP} \times 100 \tag{10}$$

Matthew's correlation coefficient (MCC) (Azar and El-Said, 2014; Fawcett, 2006) parameter is:

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FN)(TP + FP)(TN + FN)(TN + FP)}} \times 100 \tag{11}$$

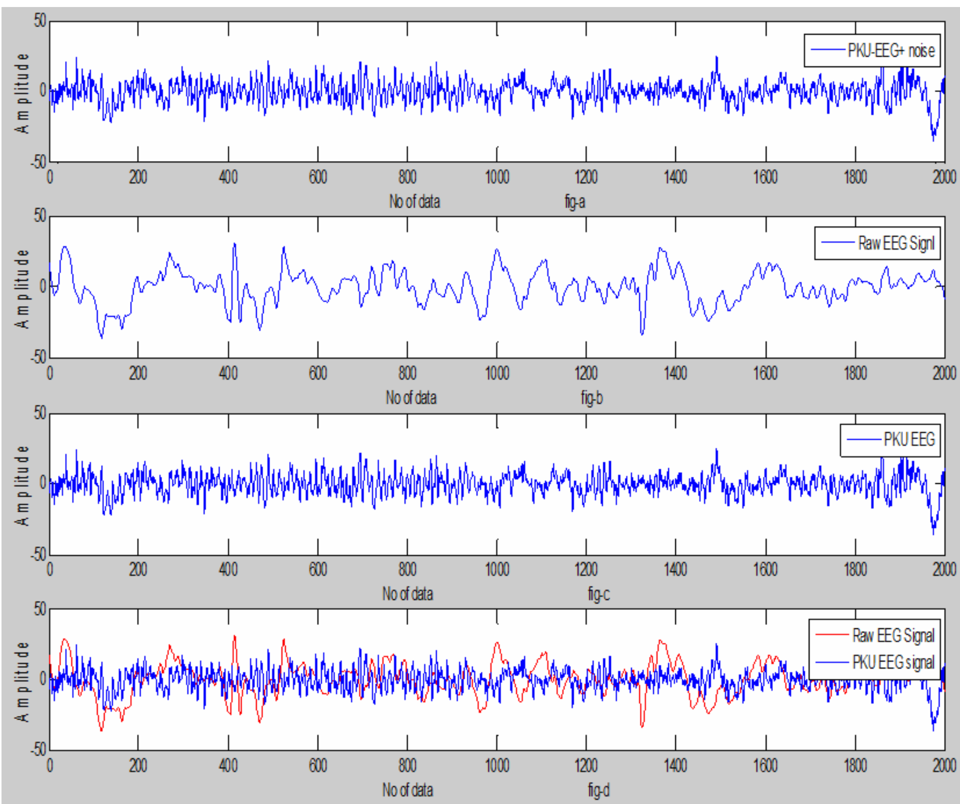
7 Result and discussion

This section presents the experimental results with the proposed method by using MATLAB R2015. Table 1 shows the patient’s information used in this work. The results of the proposed method with discrete wavelet, shearlet and CT using 300, 500, 1,000, 1,500 and 2,000 samples of window sizes are summarised in Table 2. Comparisons with the different feature extraction methods and classifiers used methods presented in Table 3, Table 4 and Table 5 are done to show the effectiveness of this technique. Six PKU affected epileptic patients EEG signals and 12 healthy non-PKU EEG signals recorded in NIMHANS Bangalore, India is used in this work. Figure 4 shows the recorded signal of PKU-EEG signal with noise raw EEG signals from healthy children and PKU-EEG signal with noise, raw EEG signal from healthy children and PKU-EEG signal with removal of noise. Figure 4(d) shows a simple comparison between PKU-EEG signal and raw EEG signal by overlapping with each other.

Table 1 Diagnostic study information

Patient ID	*Age*	*Gender*	*No. of channels*	*No. of seizure*	*Duration of seizure EEG*
1	7	F	23	7	7:10
2	7	M	23	3	2:50
3	8	F	23	7	5:40
4	7	M	23	4	4:00
5	7	M	23	5	9:00
6	5	F	21	10	2:00

Figure 4 Recorded signal, (a) PKU affected EEG signal with noise (b) RAW EEG signal (c) PKU-EEG signal (d) comparison plot between RAW-EEG and PKU-EEG (see online version for colours)



In this study, we use ANFIS trained with EGA to show how accurately our proposed method detects seizures in practice.

Table 2 Performance measurement of EGA-ANFIS (without feature extraction) DWT-EGA-ANFIS, ST-EGA-ANFIS, and CT-EGA-ANFIS using different window sizes

Window size (number of samples)	*Statistical parameter*	*Without feature extraction (WOFE) (%) (EGA-ANFIS)*	*Discrete wavelet transform (DWT) (%) (DWT-EGA-ANFIS)*	*Shearlet transform (ST) (%) (ST-EGA-ANFIS)*	*Contourlet transform (CT) (%) (CT-EGA-ANFIS)*
300	SEN	79.42	85.76	94.48	98.45
	SPE	81.63	87.23	96.89	97.95
	ACC	72.11	87.34	97.23	98.65
	MCC	75.00	83.00	93.00	96.00
500	SEN	73.82	87.26	95.45	97.81
	SPE	70.73	84.52	93.23	96.34
	ACC	68.32	88.69	96.18	97.67
	MCC	73.00	82.00	90.00	91.00
1,000	SEN	68.41	88.34	95.82	97.35
	SPE	71.45	87.82	94.67	98.32
	ACC	65.33	85.45	93.32	95.12
	MCC	72.00	83.00	89.00	96.00
1,500	SEN	65.32	86.76	93.39	97.23
	SPE	68.56	88.38	96.12	98.18
	ACC	79.31	88.76	97.98	98.00
	MCC	72.00	82.00	92.00	95.00
2,000	SEN	68.89	96.42	97.36	*99.88*
	SPE	73.23	98.38	99.78	*99.93*
	ACC	88.21	98.15	99.34	*99.82*
	MCC	81.00	92.00	95.00	*97.00*

Table 3 Accuracy comparison between our method and state of the arts

Authors	*Year*	*Features/method*	*Analysis/classification*	*ACC (%)*
Patidar and Panigrahi	2017	TQWT, correntropy	LS-SVM and alcoholism risk index	97.02
Nigam and Graupe	2004	Nonlinear pre-processing filter	Neural networks	97.20
Kannathal et al.	2005	Entropy	Adaptive neuro fuzzy inference system	92.22
Guler et al.	2005	Lyapunov exponents	Recurrent neural networks	96.94
Ataee et al.	2006	Wavelet features	Neural network	94.00
Jahankhani et al.	2006	Wavelet features	Neural network	97.00
Subasi	2007	Wavelet features	Expert system	95.00
Tzallas et al.	2007	Time-frequency analysis	Neural networks	97.73
Ubeyli	2008	Wavelet features	Expert model	96.89
Guo et al.	2010	Multiwavelet-entropy features	Neural networks	98.27
		Permutation entropy		
Nicolaou and Georgiou	2012	Time-frequency analysis and higher order statistics	Support vector machines	93.55
Alam and Bhuiyan	2013	Dual-tree complex wavelets	Neural networks	80.00
Das et al.	2014	Wavelet features and approximate entropy	Support vector machines	96.80
Kumar et al.	2014	Dual-tree, complex wavelets + inverse Gaussian	Neural networks	94.00
Das et al.	2016	DWT	Support vector machines	96.28
Orhan	2011	K-means clustering	ANN	96.67
Liu et al.	2014	WT	SVM	95.33
Ling et al.	2009	RWE	ANN	95.20
Li et al.	2017	DWT-based EA	NNE	98.78
Proposed Method		WOFE	ANFIS-EGA	88.21
		DWT	ANFIS-EGA	98.15
		ST	ANFIS-EGA	99.34
		CT	ANFIS-EGA	99.82

From the results shown in Table 2, it is found that the proposed method with CT provides high sensitivity, specificity, accuracy and MCC of 99.88%, 99.93%, 99.82% and 97% respectively than the discrete wavelet and STs. The above said information of CT-ANFIS-EGA is more clearly shown in Figures 5 to 9. Table 3 shows the accuracy values corresponding to the classification results of the recorded datasets using different transforms with different classifiers. The italic results with ANFIS-EGA are the better result as compared to existing methods as shown in Table 3. It is concluded from the Table 3 is that the proposed EGA is very much effective to train the ANFIS network. It is also clear that without feature extraction method (WOFE), the ANFIS-EGA have 88.2% of accuracy. The DWT-based EA with NNE method (Li et al., 2017) is superior to DWT-ANFIS-EGA but our proposed method of ST-ANFIS-EGA and CT-ANFIS-EGA is having more accuracy of 0.66% and 1.04% respectively.

Figure 5 Comparative analysis of SEN, SPE, ACC and MCC (300 samples) (see online version for colours)

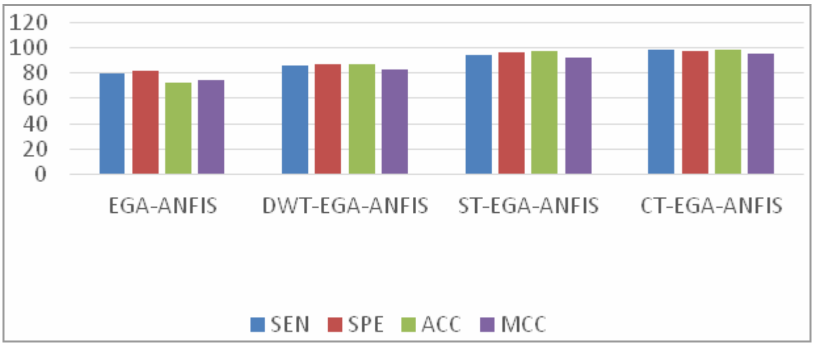


Figure 6 Comparative analysis of SEN, SPE, ACC and MCC (500 samples) (see online version for colours)

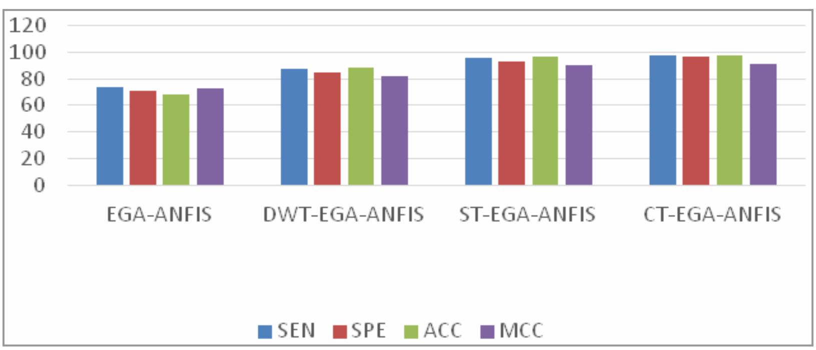


Figure 7 Comparative analysis of SEN, SPE, ACC and MCC (1,000 samples) (see online version for colours)

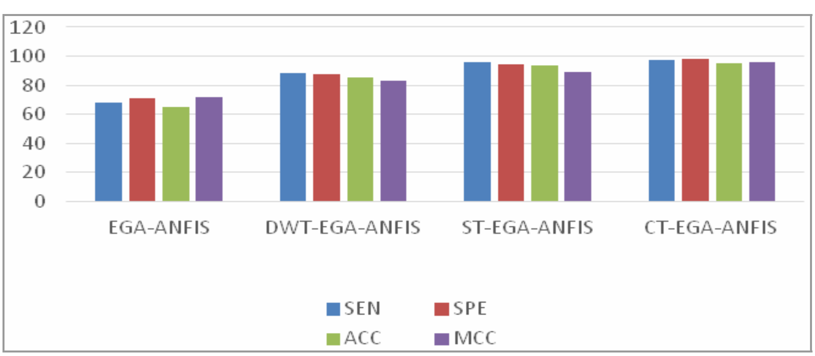


Figure 8 Comparative analysis of SEN, SPE, ACC and MCC (1,500 samples) (see online version for colours)

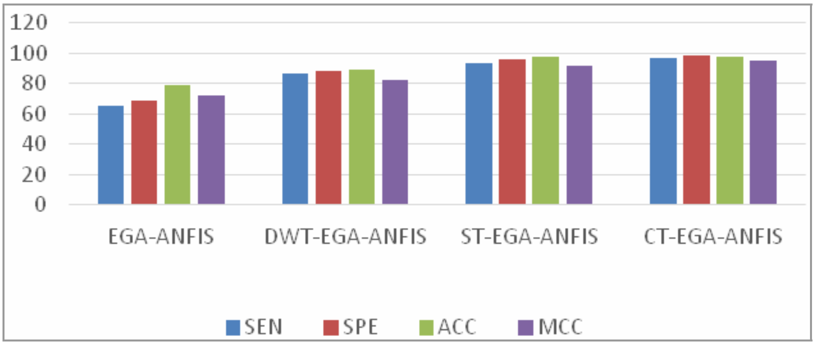
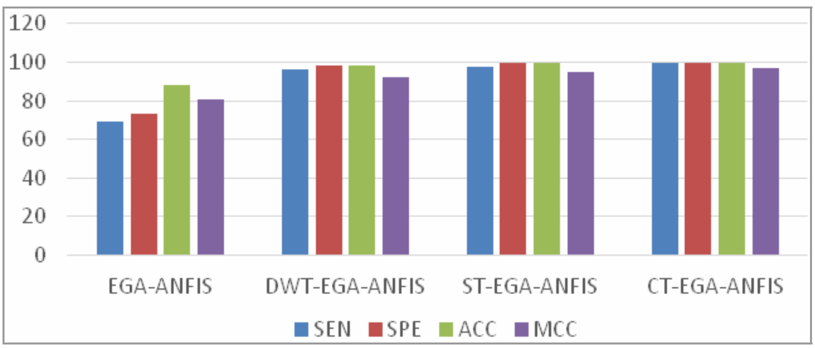


Figure 9 Comparative analysis of SEN, SPE, ACC and MCC (2,000 samples) (see online version for colours)



Similarly, Table 4 shows the sensitivity and specificity values corresponding to the classification results of the recorded datasets using different transforms with different classifiers. The italic result using ANFIS-EGA is outperforms using CTs as feature extraction methods. The proposed method using DWT performs less in sensitivity compared with Ling et al. (2009), Patidar and Panigrahi (2017), Swami et al. (2014, 2016) and Pachori and Patidar (2014). Similarly the proposed method using DWT performs less in specificity compared with other existing results (Lee et al., 2014; Chandaka et al., 2009; Patidar and Panigrahi, 2017; Swami et al., 2014, 2016). From the above analysis it is concluded that the CT-ANFIS-EGA method may be used for clinical diagnosis of PKU patients in their childhoods. In this proposed work, the real implementation of DWT, the existing ST and CT (Paulo et al., 2017) is compared with our proposed method as shown in Table 5. Different classifiers such as KNN, SVM, and RF are used for classification of epileptic seizure and non-epileptic seizure previously by the researchers (Paulo et al., 2017).

Table 4 Comparison between our and existing methods in term of sensitivity and specificity

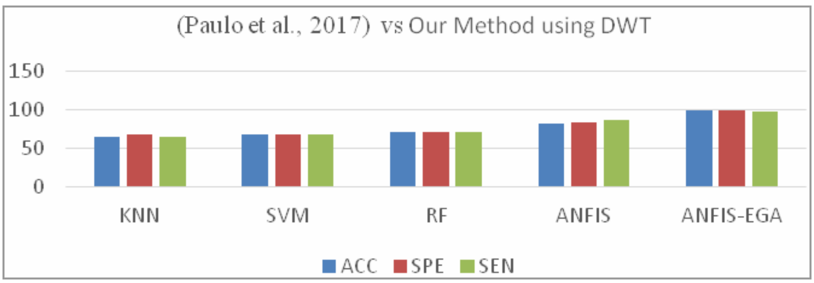
Authors	*Year*	*Methods*	*SEN (%)*	*SPE (%)*
Yan et al.	2015	Stockwell transform	94.26	96.34
Majumdar and Vardhan	2011	Differential windowed variance	89.27	91.525
Aarabi et al.	2009	Fuzzy rule-based system	68.90	97.80
Chua et al.	2011	Patient-specific seizure detection	78.00	------------
Liu et al.	2014	WT and SVM	94.46	95.26
Lee et al.	2014	Wavelet transform and NEWFM	96.33	100
Chandaka et al.	2009	SVM	92.4	98.6
Ling et al.	2009	RWE with ANN	98.17	92.12
Subasi	2007	Mixture of expert	95	94
Joshi et al.	2014	Fractional linear prediction, SVM	96	95
Patidar and Panigrahi	2017	TQWT and LS-SVM	97	99
Swami et al.	2014	WPT, standard deviation, entropy and SVM	99.21	99.34
Swami et al.	2016	DTCWT and general regression neural network	98.32	99.55
Pachori and Patidar	2014	EMD and LS-SVM	97.68	98.07
Proposed method		WOFE-ANFIS-EGA	68.89	73.23
		DWT-ANFIS-EGA	*96.42*	*98.38*
		ST-ANFIS-EGA	*97.36*	*99.78*
		CT-ANFIS-EGA	*99.88*	*99.93*

Table 5 Performance comparison of proposed method with Paulo et al. (2017)

Transform	*Classifiers*	*ACC (%)*	*SPE (%)*	*SEN (%)*	*MCC (%)*
DWT	KNN	64.50	67.00	65.00	_
	SVM	68.00	68.00	68.00	_
	RF	70.00	70.00	70.00	_
	ANFIS	81.45	83.00	86.14	88.00
	ANFIS-EGA	98.15	98.38	96.42	92.00
ST	KNN	68.00	68.00	68.00	_
	SVM	74.00	75.00	74.00	_
	RF	79.50	80.00	80.00	_
	ANFIS	83.42	84.67	88.34	88.91
	ANFIS-EGA	99.34	99.78	97.36	95.00
CT	KNN	65.50	64.00	66.00	_
	SVM	67.50	69.00	68.00	_
	RF	81.50	81.70	81.50	_
	ANFIS	86.00	88.12	91.22	93.00
	ANFIS-EGA	99.82	99.93	99.88	97.00

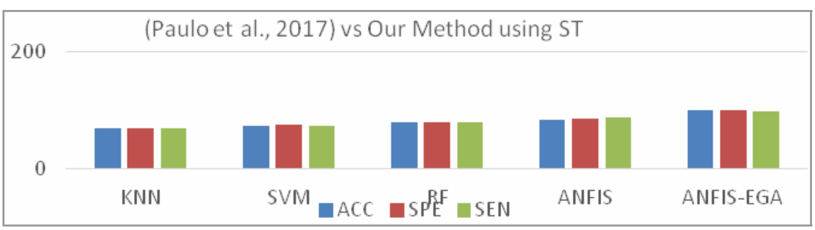
As shown in Table 5 our method outperforms than the existing outputs. For more balanced measure of classification performance, the MCC is calculated for DWT-ANFIS-EGA (92%), ST-ANFIS-EGA (95%) and CT-ANFIS-EGA (97%). From this, it is concluded that CT-ANFIS-EGA has high performance than the existing methods. Figures 10–12 shows the classifiers performance analysis of the existing method (Paulo et al., 2017) with our method for all statistical parameters using DWT, CT and ST feature extraction methods.

Figure 10 Classifiers performance analysis of existing method* vs. proposed method using DWT (see online version for colours)



Source: *Paulo et al. (2017)

Figure 11 Classifiers performance analysis of existing method* vs. our method using ST (see online version for colours)



Source: *Paulo et al. (2017)

Figure 12 Classifiers performance analysis of Paulo et al. (2017) vs. our method using CT (see online version for colours)

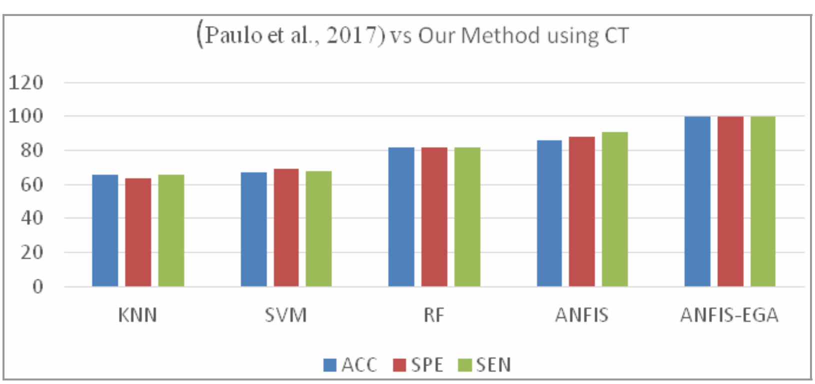


Figure 13 Plot between the original EEG and ANFIS output data of EEG signal (see online version for colours)

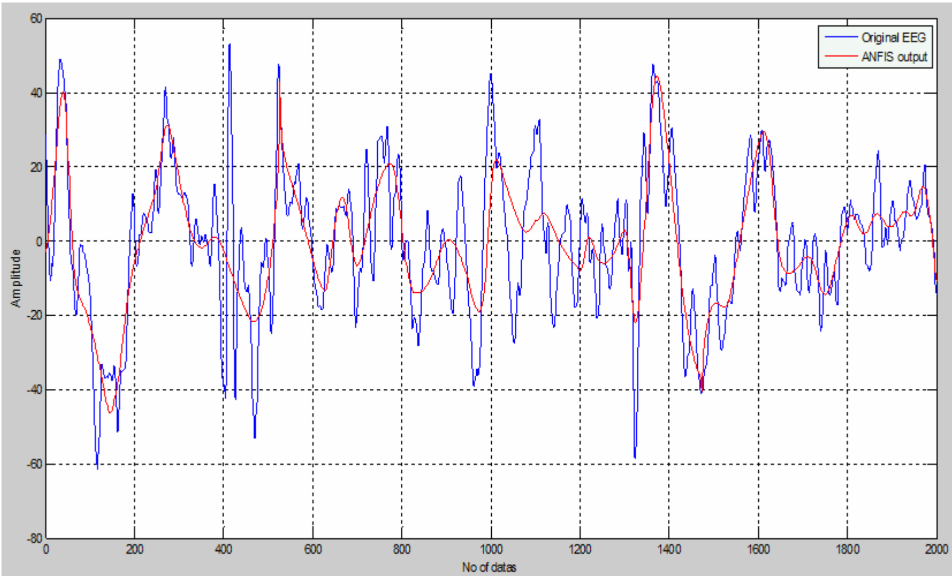


Figure 14 Plot between the original EEG and EGA-ANFIS output data of EEG signal (see online version for colours)

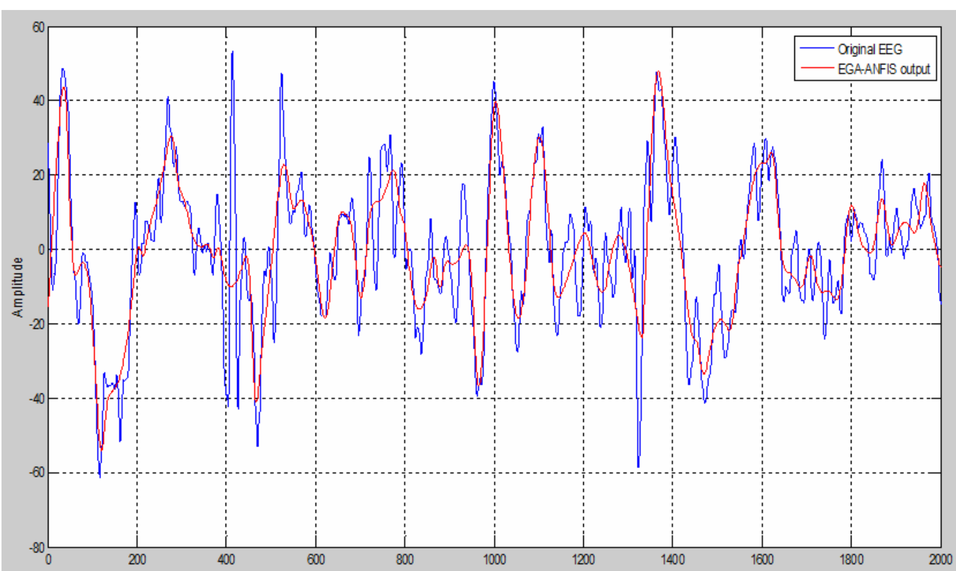


Figure 15 Plot between the original EEG and DWT-ANFIS-EGA output data of EEG signal (see online version for colours)

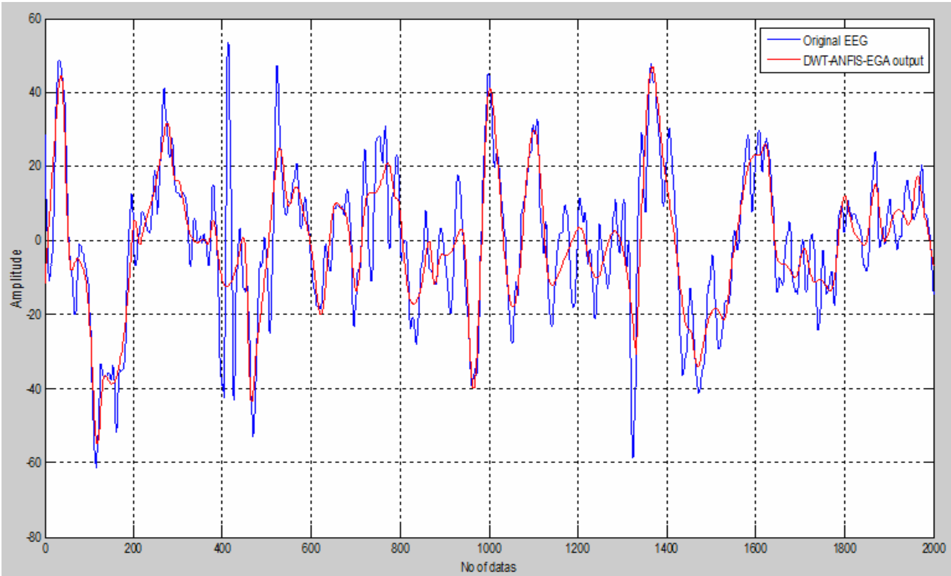


Figure 16 Plot between the original EEG and ST-ANFIS-EGA output data of EEG signal (see online version for colours)

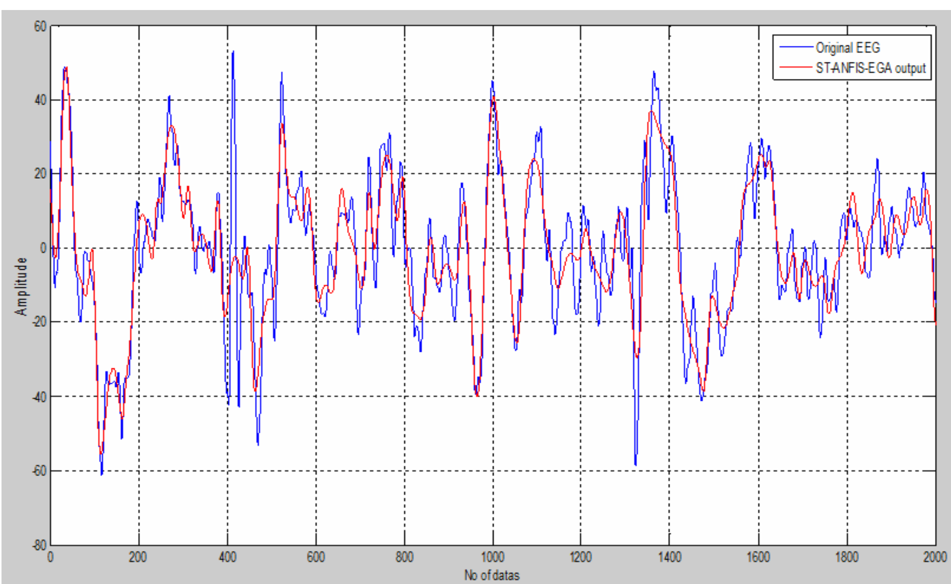


Figure 17 Plot between the original EEG and CT-ANFIS-EGA output data of EEG signal (see online version for colours)

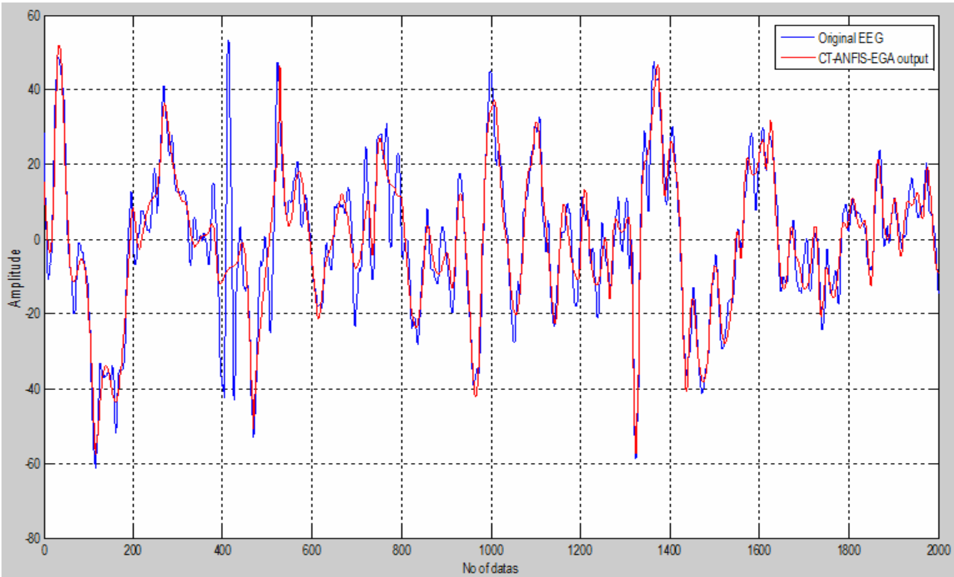


Figure 18 Error convergence curve (see online version for colours)

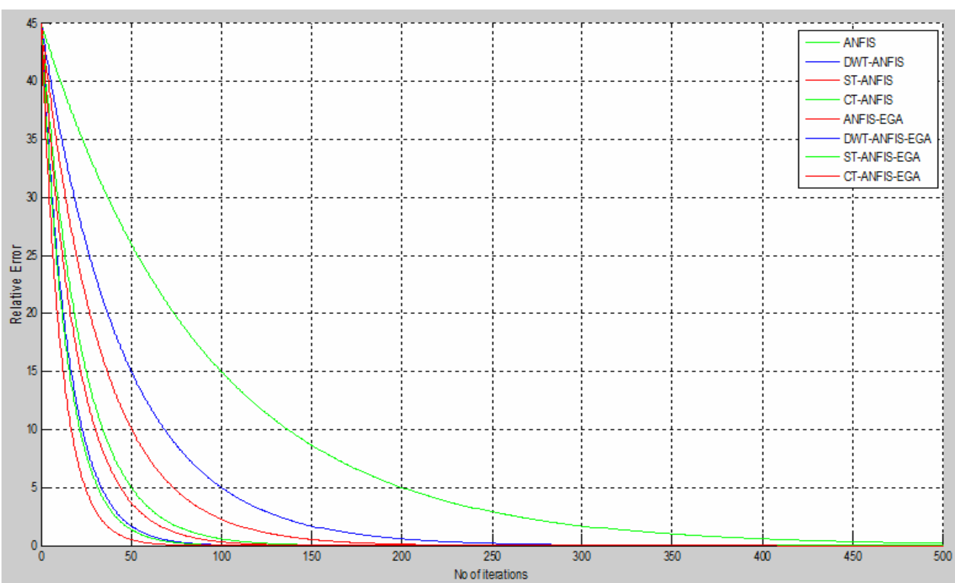


Figure 19 ROC curves and area under ROC curve obtained by the different methods (see online version for colours)

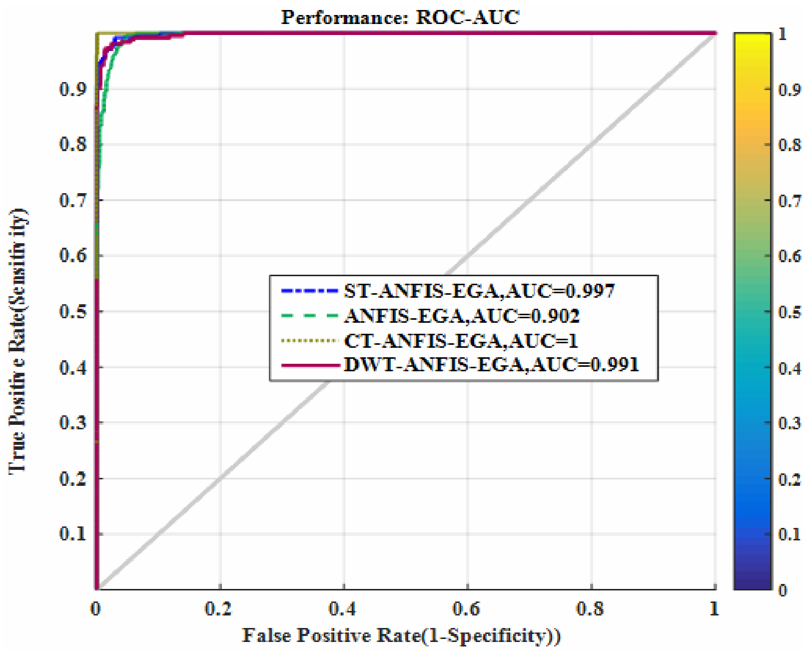


Figure 20 Scatter plot of DWT-ANFIS-EGA method (see online version for colours)

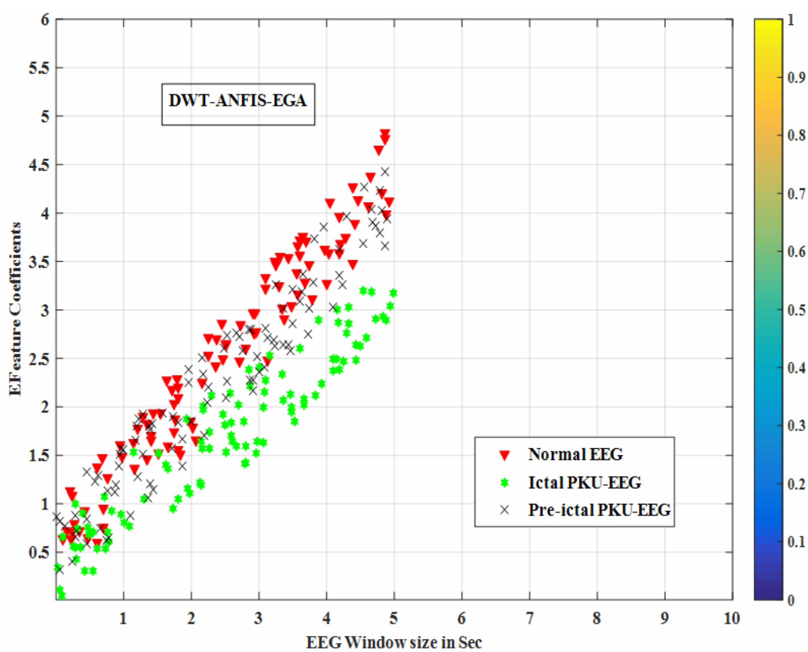


Figure 21 Scatter plot of ST-ANFIS-EGA method (see online version for colours)

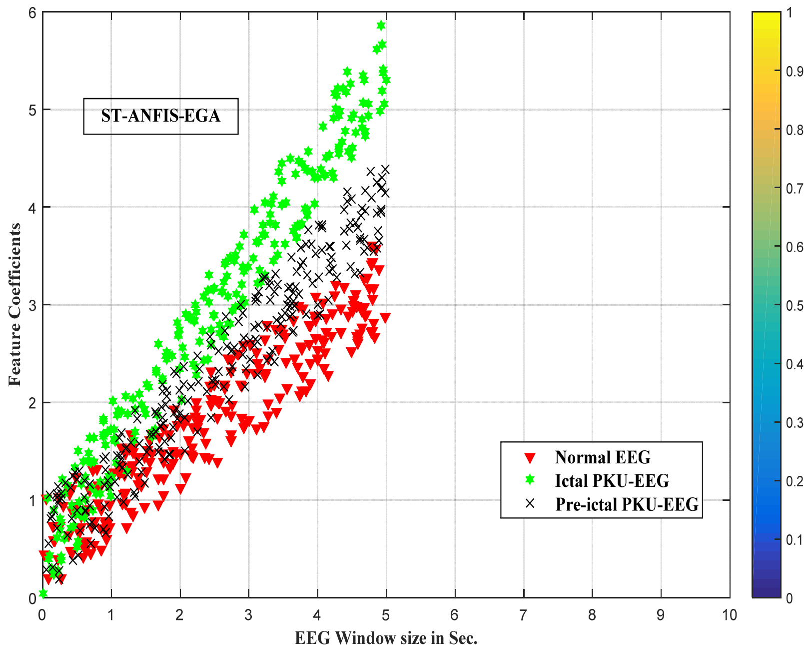


Figure 22 Scatter plot of CT-ANFIS-EGA method (see online version for colours)

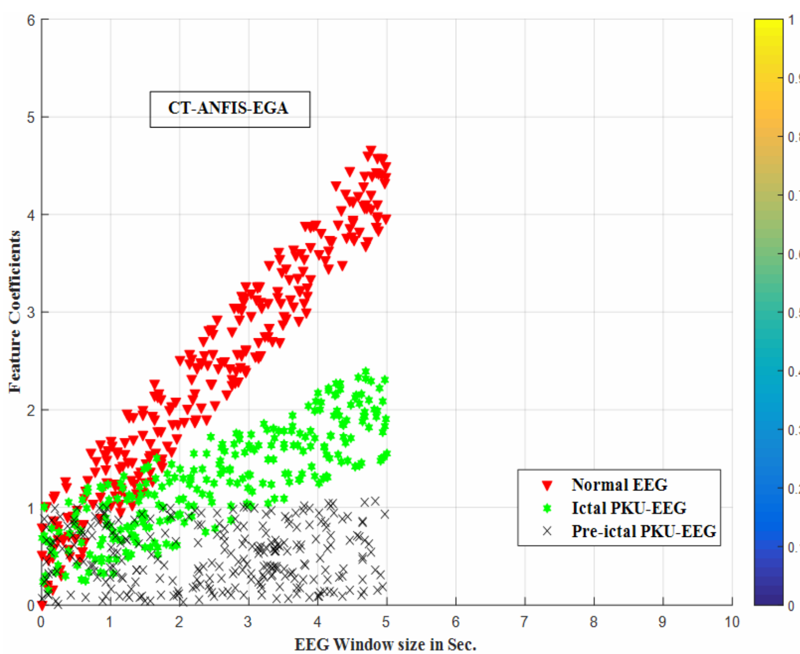
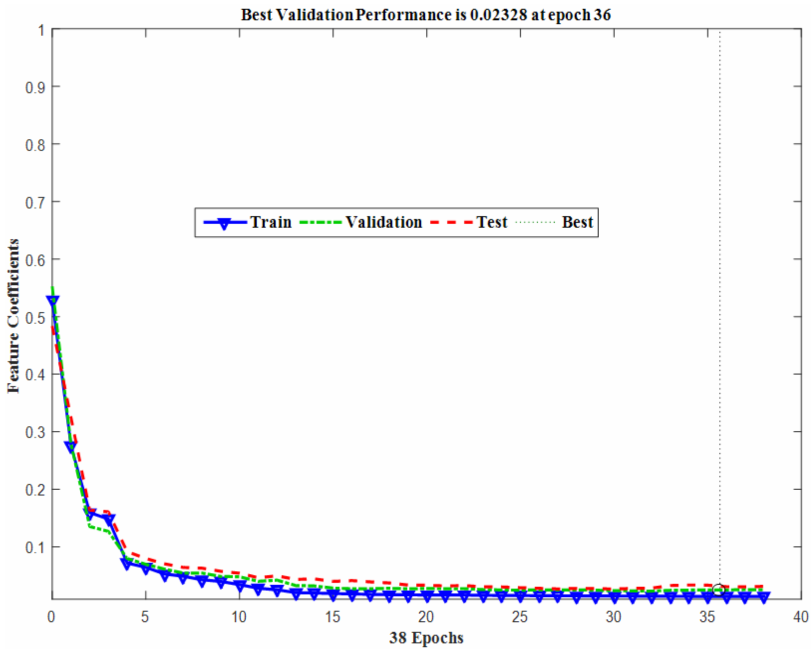


Figure 23 Best validation plot of proposed CT-ANFIS-EGA method (see online version for colours)



The MATLAB results output are shown in Figures 13 to 17 in a comparative way between original EEG or raw EEG and the proposed methods output. Finally the error convergence curve as shown in Figure 18, shows that the classification error can be minimised by our proposed method. The performance through ROC-AUC for different proposed methods is shown in Figure 19. The ANFIS-EGA method without decomposition method having AUC = 0.902. Similarly, DWT-ANFIS-EGA and ST-ANFIS-EGA methods got the AUC of 0.991 and 0.997 respectively. The CT-ANFIS-EGA method got the AUC = 1, which shows outperformance than other aforesaid methods. Figure 20 shows the scatter plot of DWT-based method in which normal EEG, ictal PKU-EEG and preictal PKU-EEG signals are classified. Figure 21 and Figure 22 shows the scatter plot for ST-ANFIS-EGA and CT-ANFIS-EGA methods respectively. From Figure 20, Figure 21 and Figure 22, it is clear that CT approached method, accurately classified the normal and PKU affected EEG signals. Due to better performance, the best validation performance was evaluated by taking 38 epochs, which shows best value of 0.02328 at 36th epoch which is shown in Figure 23.

8 Conclusions

In this proposed method, an EGA is used with ANFIS network for clinical diagnosis of PKU affected children. Several features were extracted by using DWT, ST, and CT and used as input to ANFIS classifier. The results obtained by the proposed algorithm are compared with the existing results to validate the statistical parameters of the algorithm. Proposed methods are compared with each other and it is concluded that the CT with

ANFIS-EGA have high performance. So, it may be helps for clinical diagnosis of PKU affected patients in future. In future it will be experimented on publicly available datasets.

Acknowledgements

The authors would like to thank the NIMHANS, Bangalore, India and Trident Academy of Technology for the valuable research support in terms of advanced biotechnology laboratory.

References

Aarabi, A., Fazel-Rezai, R. and Aghakhani, Y. (2009) 'A fuzzy rule-based system for epileptic seizure detection in intracranial EEG', *Clin. Neuro. Physiol.*, Vol. 120, No. 9, pp.1648–1657.

Adelui, H., Zhou, Z. and Dadmehr, N. (2003) 'Analysis of EEG records in an epileptic patient using wavelet transform', *Journal of Neuroscience Methods*, Vol. 123, No. 1, pp.69–87.

Alam, S.S. and Bhuiyan, M.I.H. (2013) 'Detection of seizure and epilepsy using higher order statistics in the EMD domain', *Journal of Biomedical and Health Informatics*, Vol. 17, No. 2, pp.312–318.

Ataee, P., Avanaki, A.N., Shariatpanahi, H.F. and Khoee, S.M. (2006) 'Ranking features of wavelet decomposed EEG based on significance in epileptic seizure prediction', *14th European Signal Processing Conference*, IEEE, pp.1–4.

Azar, A.T. and El-Said, S.A. (2014) 'Performance analysis of support vector machines classifiers in breast cancer mammography recognition', *Neural Comput. Appli.*, Vol. 24, No. 5, pp.1163–1177.

Bandarabadi, M., Teixeira, C.A., Rasekhi, J. and Dourado, A. (2015) 'Epileptic seizure prediction using relative spectral power features', *Clinical Neurophysiology*, Vol. 126, No. 2, pp.237–248.

Bhattacharyya, A. et al. (2016) 'A novel approach for automated detection of focal EEG signals using empirical Wavelet transform', *Neural Computing and Applications*, Vol. 29, No. 8, pp.134–148.

Chandaka, S., Chatterjee, A. and Munshi, S. (2009) 'Cross-correlation aided support vector machine classifier for classification of EEG signals', *Expert Syst. Appl.*, Vol. 36, No. 2, pp.1329–1336.

Chua, E.C.P., Patel, K., Fitzsimons, M. and Bleakley, C.J. (2011) 'Improved patient specific seizure detection during pre-surgical evaluation', *Clin. Neuro. Physiol.*, Vol. 122, No. 4, pp.672–699.

Das, A.B., Bhuiyan, M.I.H. and Alam, S.S. (2014) 'A statistical method for automatic detection of seizure and epilepsy in the dual tree complex wavelet transform domain', *International Conference on Informatics, Electronics & Vision*, IEEE, pp.1–6.

Das, A.B., Bhuiyan, M.I.H. and Alam, S.S. (2016) 'Classification of EEG signals using normal inverse Gaussian parameters in the dual recomplex wavelet transform domain for seizure detection', *Signal, Image and Video Processing*, Vol. 10, No. 2, pp.259–266.

Do, M.N. and Vetterli, M. (2005) 'The contourlet transform: an efficient directional multi resolution image representation', *IEEE Transactions on Image Processing*, Vol. 14, No. 12, pp.2091–2106.

Fawcett, T. (2006) 'An introduction to ROC analysis', *Pattern Recogn. Lett.*, Vol. 27, No. 8, pp.861–874.

Guler, N.F., Ubeyli, E.D. and Guler, I. (2005) 'Recurrent neural networks employing Lyapunov exponents for EEG signals classification', *Expert Systems with Applications*, Vol. 29, No. 3, pp.506–514.

Guo, L., Rivero, D. and Pazos, A. (2010) 'Epileptic seizure detection using multi wavelet transform based approximate entropy and artificial neural networks', *Journal of Neuroscience Methods*, Vol. 193, No. 1, pp.156–163.

Jahankhani, P., Kodogiannis, V. and Revett, K. (2006) 'EEG signal classification using wavelet feature extraction and neural networks', *IEEE John Vincent International Symposium on Modern Computing*, pp.120–124.

Joshi, V., Pachori, R.B. and Vijesh, A. (2014) 'Classification of ictal and seizure-free EEG signals using fractional linear prediction', *Biomedical Signal Processing and Control*, Vol. 9, pp.1–5.

Kannathal, N., Choo, M.L., Acharya, U.R. and Sadasivan, P. (2005) 'Entropies for detection of epilepsy in EEG', *Computer Methods and Programs in Biomedicine*, Vol. 80, No. 3, pp.187–194.

Kumar, Y., Dewal, M. and Anand, R. (2014) 'Epileptic seizures detection in EEG using DWT-based ApEn and artificial neural network', *Signal, Image and Video Processing*, Vol. 8, pp.1323–1334.

Lee, S-H., Lim, J.S., Kim, J-K., Yang, J. and Lee, Y. (2014) 'Classification of normal and epileptic seizure EEG signals using wavelet transform, phase-space reconstruction, and Euclidean distance', *Computer Methods and Programs in Biomedicine*, Vol. 116, No. 1, pp.10–25.

Li, M., Chen, W. and Zhang, T. (2017) 'Classification of epilepsy EEG signals using DWT-based envelope analysis and neural network ensemble', *Biomedical Signal Processing and Control*, Vol. 31, pp.357–365.

Lim, W.Q. (2010) 'The discrete shearlet transform: a new directional transform and compactly supported shearlet frames', *IEEE Transactions on Image Processing*, Vol. 19, No. 5, pp.1166–1180.

Ling, G., Daniel, R., Jose, A.S. and Alejandro, P. (2009) 'Classification of EEG signals using relative wavelet energy and artificial neural networks', *Proceedings of first ACM/SIGEVO Summit on GEC*, June, pp.177–183.

Liu, Y.X., Zhou, W.D., Yuan, Q. and Chen, S.S. (2014) 'Automatic seizure detection using wavelet transform and SVM in long-term Intracranial EEG', *IEEE Trans Neural System Rehabilitation Engineering*, Vol. 20, No. 6, pp.749–755.

Luijtellar, G.V. et al. (2016) 'Methods of automated absence seizure detection, interference by stimulation, and possibilities for prediction in genetic absence models', *Journal of Neuroscience Methods*, Vol. 260, pp.144–158.

Majumdar, K.K. and Vardhan, P. (2011) 'Automatic seizure detection in ECoG by differential operator and windowed variance', *IEEE Trans. Neural Syst. Rehabil. Eng.*, Vol. 19, No. 4, pp.356–365.

Nicolaou, N. and Georgiou, J. (2012) 'Detection of epileptic electroencephalogram based on permutation entropy and support vector machines', *Expert Systems with Applications*, Vol. 39, No. 1, pp.202–209.

Nigam, V.P. and Graupe, D. (2004) 'A neural-network based detection of epilepsy', *Neurological Research*, Vol. 26, No. 1, pp.55–60.

Orhan, U., Hekim, M. and Ozer, M. (2011) 'EEG signals classification using the K-means clustering and a multilayer perceptron neural network model', *Expert System Application*, Vol. 38, No. 10, pp.13475–13481.

Pachori, R.B. and Patidar, S. (2014) 'Epileptic seizure classification in EEG signals using second-order difference plot of intrinsic mode functions', *Comput. Methods Programs Biomed.*, Vol. 113, No. 2, pp.494–502.

Paine, R.S. (1957) 'The variability in manifestations of untreated patients with phenylketonuria (phenylpyruvic aciduria)', *Pediatrics*, Vol. 20, No. 2, pp.290–302.

Patidar, S. and Panigrahi, T. (2017) 'Detection of epileptic seizure using Kraskov entropy applied on tunable-Q wavelet transform of EEG signals', *Biomedical Signal Processing and Control*, Vol. 34, pp.74–80.

Paulo, A., Thiago, M., Dalton, F., Jorge, S. and Helio, P. (2017) 'Electroencephalogram signal classification based on shearlet and contourlet transforms', *Expert Systems With Applications*, Vol. 67, pp.140–147.

Peng, Z., Li, Z., Cai, Z. and Lin, L. (2016) 'Deep boosting: joint feature selection and analysis dictionary learning in hierarchy', *Neurocomputing*, Vol. 178, pp.36–45.

Schwartz, W.R., Silva, R.D., Davis, L.S. and Pedrini, H. (2011) 'A novel feature descriptor based on the shearlet transform', *18th IEEE International Conference on Image Processing*, pp.1033–1036.

Shivnarayan, P., Pachori, R.B., Upadhyay, A. and Rajendra Acharya, U. (2016) 'An integrated alcoholic index using tunable-Q wavelet transform based features extracted from EEG signals for diagnosis of alcoholism', *Applied Soft Computing*, Vol. 2, pp.73–84.

Song, L.J., Hu, W. and Zhang, R. (2016) 'Automated detection of epileptic EEGs using a novel fusion feature and extreme learning machine', *Neurocomputing*, Vol. 175, pp.383–391.

Subasi, A. (2007) 'EEG signal classification using wavelet feature extraction and a mixture of expert model', *Expert Systems with Applications*, Vol. 32, pp.1084–1093.

Subasi, A. and Gursoy, M.I. (2010) 'EEG signal classification using PCA, ICA, LDA and support vector machines', *Expert Systems with Applications*, pp.138–157.

Swami, P., Gandhi, T.K., Panigrahi, B.K., Tripathi, M. and Anand, S. (2016) 'A novel robust diagnostic model to detect seizures in electroencephalography', *Expert Syst. Appl.*, Vol. 56, pp.116–130.

Swami, P., Godiyal, A.K., Santhosh, J., Panigrahi, B.K., Bhatia, M. and Anand, S. (2014) 'Robust expert system design for automated detection of epileptic seizures using SVM classifier', *Proceedings of IEEE International Conference on Parallel, Distributed and Grid Computing*, pp.219–222.

Tzallas, A., Tsipouras, M. and Fotiadis, D. (2007) 'Automatic seizure detection based on time-frequency analysis and artificial neural networks', *Computational Intelligence and Neuroscience*, Vol. 80, pp.510–523.

Ubeyli, E.D. (2008) 'Wavelet mixture of experts network structure for EEG signals classification', *Expert Systems with Applications*, Vol. 34, pp.1954–1962.

Wang, X.Y., Liu, Y.C. and Yang, H.Y. (2014) 'An efficient remote sensing image denoising method in extended discrete shearlet domain', *Journal of Mathematical Imaging and Vision*, Vol. 49, pp.434–453.

Yan, A., Zhou, W., Yuan, Q., Yuan, S., Wu, Q., Zhao, X. and Wang, J. (2015) 'Automatic seizure detection using Stockwell transform and boosting algorithm for long-term EEG', *Epilepsy & Behavior*, Vol. 45, pp.8–14.

Zabihi, M. et al. (2016) 'Analysis of high-dimensional phase space via Poincare section for patient-specific seizure detection', *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 24, No. 3, pp.386–398.

Zurfluh, M.R., Zschocke, J., Lindner, M., Feillet, F., Chery, C., Burlina, A., Stevens, R.C. and Thony, B. (2008) 'Molecular genetics of tetrahydrobiopterin-responsive phenylalanine hydroxylase deficiency', *Hum. N. Mutat.*, Vol. 29, pp.167–175, Wiley Online Library.