Epileptic Seizure Detection in EEG Signal using Discrete Stationary Wavelet-Based Stockwell Transform

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ABSTRACT:
Epilepsy is a neurological disorder occurs at the central nervous system, Electroencephalography (EEG) is the reliable tool for analysing the human brain activity with the help of the signals, moreover, it plays a significant role in the detection of epileptic seizures. The abnormal electrical discharge leads to loss of memory; from the recent survey over five crore people are affected by epilepsy. An effective detection system is a vital solution for detecting the epileptic disease in the initial stage. In this paper, an improved epilepsy seizure detecting system is developed with a better accuracy; the EEG signal in both time and frequency domain with the use of Discrete Stationary wavelet-based Stockwell transform (DSWST) is proposed. The feature extraction is processed by a temporal feature, spectral feature and Amplitude Distribution Estimation (ADE) from EEG signals in which the normal EEG signals will have various spectral and temporal centroids. Also, a modified filter bank based particle swarm optimization (MF-PSO) helps for the feature selection; it significantly improves the classifier accuracy. Finally, a Hybrid K nearest support vector machine (Kn-SVM) is employed for classification to investigate the performance of feature to classify the brain signals into three groups of normal (healthy), seizure free (inter-ictal) and during a seizure (ictal) groups.

KEYWORDS: Epilepsy Seizures, Electroencephalography, Support Vector Machine, Discrete Stationary Wavelet Based Stockwell Transform (DSWST), Modified Filter Bank Based Particle Swarm Optimization (MF-PSO), Hybrid K Nearest Support Vector Machine (Kn-SVM).

1. INTRODUCTION

Epilepsy is a central nervous system (neurological) disorder that affects 1 % of the whole human population (Mormann et al. 2006). Epileptic seizures may cause sudden death. Unfortunately, the occurrence of epilepsy seizure founds to be unpredictable. The analysis over the electroencephalogram graph (EEG) records gives a most useful data over a brain disorder by recording the electrical activities of the brain, based on the location of the electrodes placed over the scalp and intracranial. Anyhow, recording the EEG for the longer time is expensive and intensive. Therefore, the need for automatic seizure detection is increased, to safeguard the system information. This work is developed to improve the accuracy of the classifier to predict the Epileptic seizures depend on the sub-bands. The motive is to present a new model based on the ST transform. Usually, the ST transform is a time and frequency domain which could cover the advantages of both wavelet transform (WT) and short-time Fourier transform (FT). It rectifies the translation-invariance demerits over the discrete wavelet transform (DWT). In the proposed work, the Discrete Stationary Wavelet Transform (DSWT) will consider only the upsampling of the filters instead of decimating the wavelet coefficient. Due to the size of the data, it will not be affected by the transform. By eliminating the downsampling, the approximate coefficient will be preserved. In this work, the EEG signal is processed in both time and frequency domain.

In Epilepsy, there are spontaneous seizures which may last for few seconds up to 2 minutes. The different frequency band are stated below

1) Delta Waves (0.5 - 4HZ) – It represents the brainwaves are slow, loud with low frequency and deeply penetrating.

2) Theta Waves (4HZ - 8HZ) – It will act as a gateway to learning and memory. Usually, it occurs during sleep and deep meditation.

3) Alpha waves (8 HZ- 12 HZ) – It aid calmness, alertness, Mental coordination.

4) Beta waves (12HZ -26 HZ) – It controls over our consciousness. It will be more active when we are alert, attentive and making a judgment.

5) Gamma Waves (26 HZ to 100 HZ) – This is the faster brain waves; it is possible to process the information from multiple brain area at the same time. It can be accessed only at the time that the brain is calm [19].

Usually, the EEG signal is non-uniform, and also it contains transient characteristics, the time and frequency domain cannot be analyzed simultaneously. To overcome this limitation, the WT is applied for physiological signals to analyze irregular patterns.

The primary objectives of the proposed system are,

• To perform noise removal on the EEG signal at pre-processing step.

• To extract the features from the pre-processed signal.

• To classify the features of the signal and detect the disease.

This section deals with the existing technique related to the proposed research. Kalbkhani has presented a classification method for the epileptic phase based on the five sub-bands got from ST. For feature extraction process, kernel principal component analysis was used, from that, the feature vector was extracted. In the end, the weighted linear combination was applied. Eventually, the subbands were analyzed for the nearest neighbor classifier [5]. Mohammadpoory, et al. discussed about weighted visibility graph entropy (WVGE) to identify seizure from the EEG signals. This feature extraction based on WVGE improves the classifier to group the stage of diseases. This paper was evaluated by different classifiers such as SVM, K-NN, DT and NB. From the simulation results, it shows that Decision Tree classifier performs well with the WVGE [7]. Shiao, et al. proposed an approach called data analytic modeling for predicting epileptic seizures from the intracranial electroencephalogram (iEEG). In addition, a SVM based classifier technique was used. From the experimental results, the proposed system achieved robust prediction of pre-ictal and Inter-ictal EEG segments [12]. Bhattacharyya investigates a multi-variation approach for specific Seizure Detection by EEG signals. This paper proposed an empirical wavelet transform (EWT). The join features were computed to obtain better discrimination of seizure [2]. Subasi, et al. has suggested two hybrid for epileptic seizure detection based on GA and PSO, with SVM classifier. In addition, kernel parameters setting for SVM provides effect in the classification accuracy. Initially the EEG signal was decomposed into time and frequency sub bands using DWT and made a statistical feature extraction. From this study, it proves the hybrid technique leads in performance, but it takes longer execution time due to the parameter selection process [14]. Truong, et al. proposed an automatic channel selection (ACS) engine to determine most informative iEEG recordings. The ACS engine contains supervised classifier to find iEEG channels. In this process also the feature extraction was carried out in time and frequency domain [XVI]. Mursalin, et al. has developed a method for predicting the epileptic seizure by the EEG Signals based on the Correlation-based Feature Selection method (ICFS) with Random Forest classifier (RF). In which the standard deviation plays a vital role in feature selection [9]. Wang et al. has suggested a partial directed coherence (PDC) analysis for detecting Epileptic Seizure with the use of EEG signals. Initially the multivariate model was established for the intensity of information based on the PDC analysis. In this ANN with SVM classifier was added based on error backpropagation for detecting epileptic seizure [18]. Satapathy, et al. analysed an epileptic disorder by EEG signals by integrating best attributes of Artificial Bee Colony (ABC) and radial basis function networks (RBFNN). The potential features were extracted from the signal by using DWT techniques. The modified ABC algorithm has trained the RBFNN for classification [11]. Gomathi, et al. provided a research idea by analysing an EEG signal for detecting brain diseases. In this, K means clustering algorithm which is used for distinguishing various diseases in human brain. Backpropagation method was used for classification [4]. Ur Rehman suggested an algorithm to make empirical mode decomposition for processing of multichannel signals. In this work, a multivariate empirical mode decomposition algorithm was proposed. Also, a filter bank was added to the proposed system, group of bandpass filter isolates various frequency bands from input signals [17]. Garrett, et al. has presented a survey based on the various methods for EEG signal classification. The SVM classifier was used for classification. Normally the SVM algorithm has good statistical learning theory, and it ensures the optimal decision function for group of training data. The authors proved that outcome from the linear and non-linear were more or less same. But the use of SVM provides a better result in classification [3]. Adam, et al. has suggested a feature selection and classifier based on particle swarm optimization (PSO), in that different version of PSO was analysed for study. This proposed selection scheme offers good peak detection and high classification rate. The standard PSO was developed as a random asynchronous particle swarm optimization [1]. Staudinger suggested a survey on complexity based EEG features for diagnosing Alzheimer’s, a kind of brain disease. These measures include spectral entropy (SE), Higuchi fractal dimension (HFD), Zero crossing rate (ZCR) and spectral centroid. The Spectral Entropy (SE) was processed under a power spectral density (PSD). In that ZCR was the rate which the signal changes the signs. The features were used to be trained in neural network. This author suggested that the combining this feature with the feature vector will improve the classification accuracy [13]. Karimoi suggested a new signal processing method for classifying epileptic seizures. Hyperbolic tangent produces unique and approximate constants pattern for segments of sets. For each of the point, hyperbolic tangent will analyze, and segregate the EEG samples as Ictal or normal. This algorithm will reduce the time complexity [6].

In this paper, the different techniques involved in the diagnosis of epileptic seizures is examined and compared the results with other existing analysis. In section 2 the proposed system development for classifying the epileptic seizures disease is described. In section 3 the results of the proposed by comparing with some existing works are discussed. In section 4, the methodologies presented in this paper are summarized.

2. MATERIAL AND METHOD

The dataset of the EEG signal is obtained from the various conditions of the patients such as healthy, during or absence of seizure. The healthy subjects obtained from the EEG recordings are denoted as Z, O and for evaluating the performance of the proposed system four classification problems are considered including; normal (N) , epileptic seizure (ES), ES and non-seizure (NS), ES and seizure-free (SF), N, ES, and SF, By combining the subsets Z and O by the class N. To obtain SF the subsets N and F are categorized.

In this work, the input EEG signal is pre-processed by the help of Discrete Stationary Wavelet-based Stockwell transform. In that, approximate and detailed coefficient is obtained from the DWT coefficient. The ε-circular shift is performed and the Fourier transform will find the real and imaginary terms. The feature extraction process will improve the resolution of the signal. It estimates energy distribution of the system, in this process zero crossing rate and short-term energy is introduced to process under temporal features. Then the amplitude distribution features, will analyse the peak signal for the sub bands. The feature selection helps to choose the best feature for classification, for this filter bank based on PSO is utilized. At last, the classifier is performed by a k- nearest neighbour based support vector machine.

2.1. Pre-Processing

Under this stage, the EEG signal is computed by a DSWST; hence this method is proposed with a stationary wavelet transform (SWT) and the discrete Fourier transform (DFT). Usually, the ST provides great frequency and time resolution even at the lower frequencies. Moreover, it accesses all frequency components without any digital filters.

2.2. ε –decimated DWT

The SWT is proposed with averaging the variants of DWT, called ε -Decimated DWT. For decomposition process the selection of odd or even concerns in every step. In ε -Decimated DWT process, the predefined indexed element will be selected instead of selecting even concerns. In this, we perform all the different possible decomposition of the original signal for maximum level J. Every decomposition is labelled by a sequence of 0 and 1, namely $\varepsilon = \varepsilon_1, \varepsilon_2, \ldots \ldots \varepsilon_j$.

Algorithm 1: Discrete Stationary wavelet based Stockwell Transform

Input: Input EEG Signal X
Output: Transformed Signal S

Procedure:

Step 1: Initially discrete Stationary wavelet transform performed using discrete wavelet transform followed by shift invariant in wavelet.

Step 2: the discrete wavelet transform is defined as,

$$\left[App_{dwt}{}^{jk}, Det_{dwt}{}^{jk}\right] = \int_{-\infty}^{\infty} x(t)\ \psi_{j,k}(t)\ dt \quad (1)$$

$$\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\psi\left(\frac{t-k2^j}{2^j}\right) \quad (2)$$

$\psi_{j,k}(t) - Mother\ Wavelet,$

Where, $x(t) - input\ signal\ in\ time\ series$
$j - Scale\ parameter,\ k - shift\ parameter$

Step 3: perform a ε-circular shift of the wavelet transformed result for ε-decimated range (up sampling mode),

$$App_{swt} = wshift('1D', App_{dwt}, \varepsilon); \quad (3)$$

$$Det_{swt} = wshift('1D', Det_{dwt}, \varepsilon); \quad (4)$$

$$swt_{coeff}(t) = [App_{swt}\ Det_{swt}]; \quad (5)$$

Step 4: the stationary ST can be represented as,

$$S(t,f) = swt_{coeff}(t)e^{-j2\pi f} \quad (6)$$

Step 5: The N-point discrete Fourier transform (DFT) is given by,

$$X\left[\frac{k}{NT}\right] = \frac{1}{N}\sum_{n=0}^{N-1} x(nT)e^{-\frac{j2\pi kn}{N}} \quad \text{k=0, 1,., N-1} \quad (7)$$

Step 6: the ST of the signal, $x(nT)$,

$$S\left[mT, \frac{n}{NT}\right] = \sum_{k=0}^{N-1} X\left[\frac{k+n}{NT}\right]\ swt_{coeff}(t)\, e^{-\frac{j2\pi kn}{N}} \quad (8)$$

m, n =0, 1, …., N-1.

Step 7: the ST is complex valued signal and represented by its amplitude,

$$|S| = \sqrt{(Re\{S\})^2 + (Im\{S\}^2} \tag{9}$$

The Discrete stationary Wavelet Transform (DSWT), is developed by combing the stationary wavelet transform and Fourier transform. The primary objective of the stationary wavelet transform is de-noising. The principle is to obtain average several de-noised signals by applying the approximate coefficient to the ε - Decimated DWT. The DWT is utilized with periodic extension and set the maximum decomposition level as J.

Initially, discrete Stationary wavelet transform has performed using discrete wavelet transform followed by shift invariant in wavelet. After processing the discrete wavelet transform, the approximate and detailed coefficient values will be obtained. By considering the upsampling mode, a ε-circular shift of the wavelet transformed will be performed. The wavelet transform is performed for the upsampling method for one-dimensional discrete stationary wavelet analysis. Then the discrete Fourier transform is computed, and the signal is differentiated as real and imaginary terms. Fig. 1 illustrates the input EEG signals used for the proposed work.

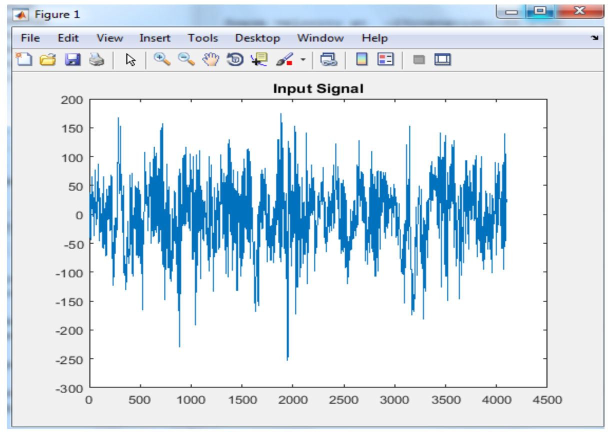

Fig. 1. Input EEG signal.

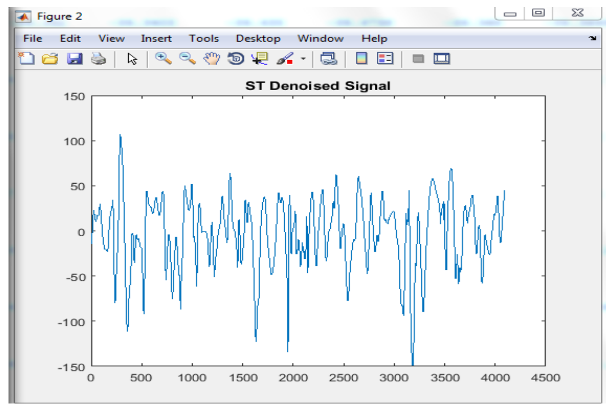

Fig. 2. ST denoised signal.

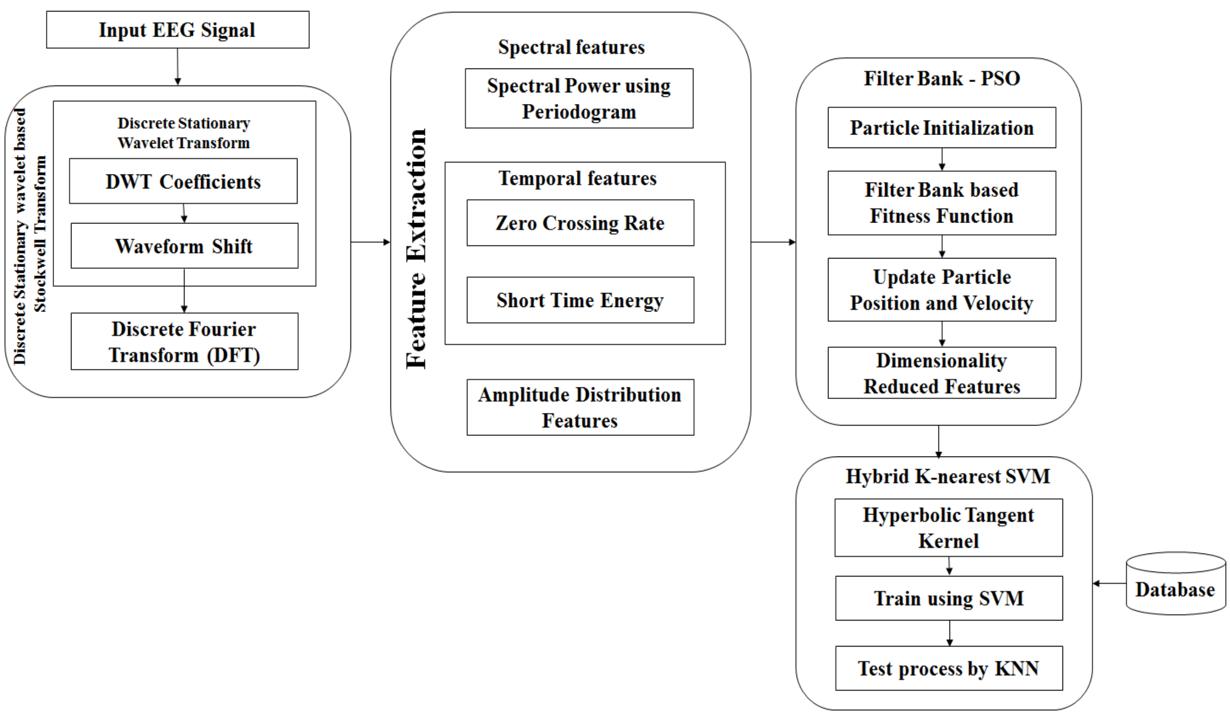

Fig. 3. Flow chart for the proposed method.

2.3. Feature Extraction

The feature extraction for EEG signal is mostly based on the signal energy distribution under time and frequency domain. In this proposed work, the feature vector is based on spectral feature, temporal feature and amplitude distribution estimation. The main motive of the spectral analysis is to characterize the average power at a frequency in the signal. Under that the spectral power is calculated based on the Periodogram, this method provides reasonably high resolution for sufficient long data length. This analysis is carried out in a way that Periodogram used as an estimator of the Power Spectral Density. In which the random signal has finite average power and therefore, can be characterized by an Average power spectral density.

Algorithm 2: Feature Extraction

Spectral Features:
Spectral power using Periodogram Method,

$$PSD\ (f) = \frac{|(\int_{-\infty}^{\infty}(S_x * W)e^{-2\pi i x \varepsilon}dx)|^2}{L} \text{ x } \frac{1}{\Delta f} \qquad (10)$$

Where, S- Stationary wavelet transform, W- applied window function, L-number of samples in the time and frequency domain, Δf -frequency interval.

Temporal Features:
Zero Crossing Rate,

$$zcr = \frac{1}{L-1}\sum_{m=1}^{L-1} 1_{R<0}(S_m S_{m-1}) \qquad (11)$$

Short Term Energy,

$$E_T = \sum_{x=-\infty}^{\infty} S^2(x) \qquad (12)$$

Additionally, the Temporal feature provides an excellent resolution for EEG. The temporal and spectral features contribute to the efficient accuracy over the classification of EEG signals. In this process, zero crossing rate and sort term energy are analyzed. The Zero-crossing rate (ZCR) can be represented as a change in signal of its sign; this can be defined as a time domain measure of signal complexity. The short-term energy (STE) is stated as a sum of the square of every sample in the segment. This will measure the change of amplitude of the signal. In the end, amplitude distribution features will be processed by the five sub band. It will analyze each band, and find out the peak value for individual Frequency bands.

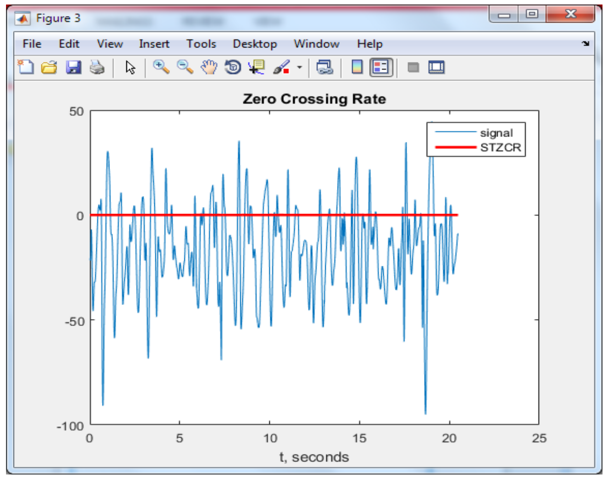

Fig. 4. Zero Crossing Rate .

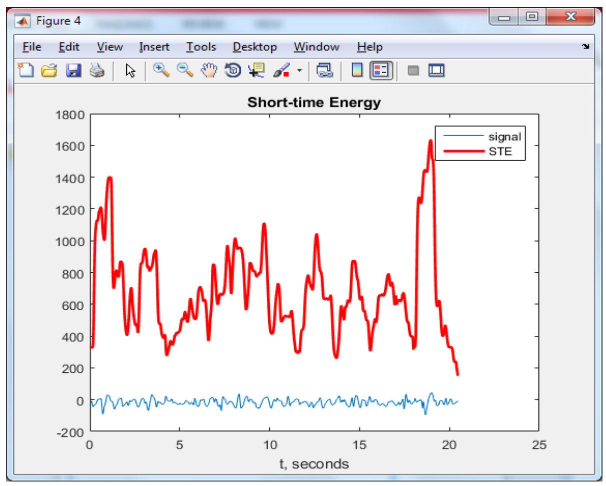

Fig. 5. Short Time Energy.

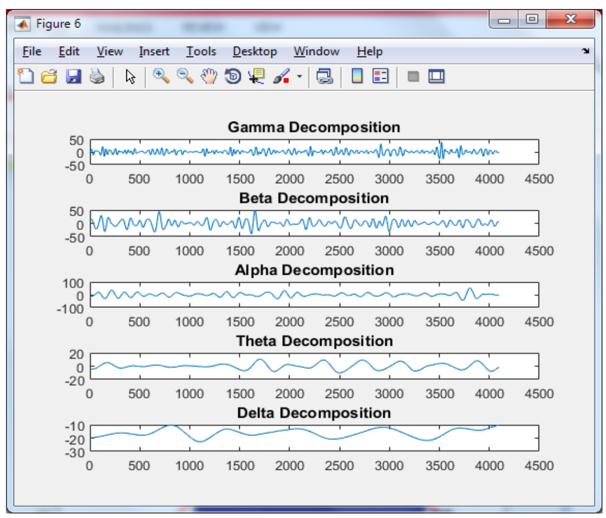

Fig. 6. Decomposition of band limited EEG into five sub bands.

2.4. Feature Selection

This process helps to find the best feature for classification process; this can be obtained based on the best value of the provided class of the given signals and the best distinction between classes. We used a particle swarm optimization added with a novel filter bank to reduce the dimensionality of the data. The EEG data of each channel will be digitally filtered, in this proposed work PSO is developed to find the optimal threshold values for each peak model. For this, the fitness function is estimated based on the filter bank. The fitness feature will be evaluated by a circular shift of the test feature and compared with the median test features. Once it satisfies the local best value will be updated then simultaneously global best value will be updated by checking the position and velocity of the particles.

Algorithm 3: Modified filter bank based Particle Swarm Optimization

Input: Test feature $\boldsymbol{Test_{fea}}$

Output: Best feature $\boldsymbol{Best_{fea}}$

Procedure:

Step 1: Initialize the particles,

Part= $Test_{fea}$,

$P_{pos} = rand(1, Part)$,

$V_{pos} = rand(1, Part)$,

Iter=100,

$P_{pos} - position\ of\ the\ particle$

$V_{pos} - velocity\ of\ the\ particle$

Iter – maximum iteration,

Step 2: $for\ i = 1\ to\ iter$ // for loop for iteration

For p=1 to all particle// for loop for each particle

Step 3: Estimate fitness function based on the filter bank, where the features are decomposed into meaningful components which is performed in each sub band,

$$Fitness_{fea}1 = circularshift(\boldsymbol{Test_{fea}} > meadian(\boldsymbol{Test_{fea}}))$$

Step4: Update the local best particles

if $Fitness_{fea}1$ is better than $Pbest$

$Pbest = Fitness_{fea}1$

End if

End for

Step 5: Update the global best particles

$P_{gbest} = Pbest$

(best in Pbest which is based on the maximum of the local best particle)

Step 6: Update the particle position and velocity,

For p=1 to all particle

$$V_{pos} = V_{pos} + (c1 * rand * Pbest - part) + (c1 * rand * P_{gbest} - part)$$

$$P_{pos} = P_{pos} + V_{pos}$$

End for

End for

2.5. Classification

After feature selection, the classifier with discrete output as healthy or inter-ictal or ictal. In this proposed work, a Hybrid K-nearest based support vector machine is developed for classification. In this work, an SVM classification based on hyperbolic tangent function is used as kernel function,

$$k(\vec{x_i}, \vec{x_j}) = \tanh(k\vec{x_i}.\vec{x_j} + c) \qquad (13)$$

The support vector machines (SVMs) are developed based on the computational learning theory. Due to the accuracy and ability to deal with a large number of predictors, in addition to that K-nearest support vectors are analysed. In that test, the process is performed in a K- nearest neighbour, instead of considering the entire nearest members. The main motive of combining K nearest to SVM is to reduce the time complexity. For this process, the SVM is integrated at the training place and KNN at the testing process.

3. RESULTS AND DISCUSSION

The classification problem is segregated into four section,

1) The first classification problems contain normal and ES signals. This system will classify the EEG signals for finding the patients out of epileptic patients and normal patients.
2) The second classification problem will consider the SF and ES EEG signals, which helps to find the epileptic seizure of the patient.
3) The third classification problem helps to analyse the normal, seizure and S-F signals.
4) The fourth classification problem considers the performance of normal, seizure and S-F signals. It helps to analyse the activities of the epileptic seizure. The details provided here are summarized in Table 1.

Table 1. Classification problem with various classes of condition.

Classification Problem	Classes	Number of EEG signals
1	Normal (Z,O) Seizure (S)	200 100
2	Seizure-free (N,F) Seizure (S)	200 100
3	Non-seizure (Z,O,N,F) Seizure (S)	400 100
4	Normal (Z,O) Seizure-free (N,F) Seizure (S)	200 200 100

Table 2. Performance measure of the proposed work for different classification classes.

	Accuracy	Sensitivity	Specificity	Precision	Recall	F-Score	Jaccard Coefficient	PPV	NPV	MCC
ZO-S	100	100	100	100	100	100	100	100	100	1
NF-S	99.639	99.7512	99.7512	99.3506	99.7512	99.5485	99.1019	99.3506	99.3506	0.991
ZONF-S	99.441	99.335	99.5554	99.0671	99.335	99.1994	98.412	99.5187	99.0671	0.9874
ZO-NF-S	99.2453	98.1768	99.0741	99.375	98.1768	98.7593	97.5518	99.5275	99.375	0.9807

The proposed system performance is evaluated under different physical parameters such as Accuracy, sensitivity, specificity, Precision, Recall, F-score, Jaccard coefficient, negative predictive value (NPV), positive predictive value (PPV), Matthews correlation coefficient (MCC) (Tiwari et al. 2017). Table 2 shows that the accuracy, prediction and predictive rate is significantly high for the first classification problem class. The Rest of the class performance also looks to be superior; hence the proposed system proved better results for finding the different classification classes.
Table 3 shows different existing work which has been compared with the proposed system, in this, the accuracy of the system is evaluated under a first classification class. Table 4 shows the comparative analysis of the proposed work by considering the second classification class by considering SF and ES signals.

Table 3. Performance analysis of normal and Seizure classes.

Method	Classification task	Accuracy (%)
1D-LBP	Z-S	99.5
PCA-ICA-LDA	Z-S	99.5
EMD	Z-S	100
Approximate Entropy	Z-S	100
CVANN- DTCWT	Z-S	100
HHT-SVM	Z-S	99.13
Time Freq,RD-STFT	Z-S	99.8
Phase correlation	Z-S	100
DTCWFT	ZO-S	100
MWT	Z-S	99.85
AESD	Z-S	99.6
Genetic Algorithm	Z-S	99.2
Combined TF feature	Z-S	100
L-SVM	Z-S	100
MPNN	Z-S	100
ANN	Z-S	100
LS-SVM	Z-S	100
WPE feature extraction	Z-S	100
DoG-LBP-SVM	ZO-S	100
Proposed System	**ZO-S**	**100**

Table 4. Performance analysis of seizure-free and epileptic seizure signals.

Method	Classification task	Accuracy (%)
FLP	NF-S	95.33
1D-LBP	NF-S	97
Local Binary Pattern	NF-S	98.33
Intrinsic mode function	NF-S	95.75
RD-STFT	F-S	94.9
DoG-LBP-SVM	NF-S	99.45 (0.25)
Proposed System	**NF-S**	**99.639**

Table 5. Performance analysis of normal, S-F, and ES signals.

Method	Classification task	Accuracy (%)
Neural network	Z-F-S	96.6
1D-LBP	Z-F-S	95.67
Recurrence quantification	Z-F-S	95.6
Non-linear parameter	ZO-NF-S	95
Cumulant feature	Z-F-S	98.5
CVANN	Z-F-S	99.3
DTCWT	ZO-NF-S	98.28
Genetic programming	Z-F-S	93.5
K-means cluster	ZO-NF-S	95.6
MPNN	Z-F-S	96.67
ANN	ZO-NF-S	97.72
Time and frequency analysis	Z-F-S	99.28
Non-linear & wavelet based	Z-F-S	99.7
Automated Diagnosis	ZO-NF-S	98.1
PCA	Z-F-S	99
High Order Spectra	Z-F-S	93.11
Frequency domain parameter	Z-F-S	93.3
DoG-LBP-SVM	ZO-NF-S	98.80
Proposed System	**ZO-NF-S**	**99.2453**

Table 5 illustrates the performance of the proposed by considering the accuracy under the third classification class. It shows that the accuracy level of the proposed work is high as compared with other existing works.

Table 6 Performance analysis for non-seizure and ES signals.

Method	Classification task	Accuracy (%)
CVANN- DTCWT	ZONF-S	99.15
RD-STFT	ZONF-S	98.1
DTCWFT	ZONF-S	100
MWT	ZONF-S	98.27
AESD	ZONF-S	97.77
MPNN	ZONF-S	99.6
ANN	ZONF-S	97.73
DWT	ZONF-S	96.65
DoG-LBP-SVM	ZONF-S	99.31 (0.17)
Proposed System	**ZONF-S**	**99.441**

In table 6, accuracy of the proposed work is compared with the existing work. In that the accuracy level for the proposed level is high by comparing all other existing techniques. From the analyses obtained from Table 3 to 6, the proposed system performance is superior in all classification classes.

The results represent the proposed work provides an efficient EEG based on computer aided diagnosis of epilepsy. Fig. 7 illustrates the comparative analysis for the accuracy of proposed system with existing works like DoG-LBP-SVM and LBP methods. In all class of classification, the proposed system performs well

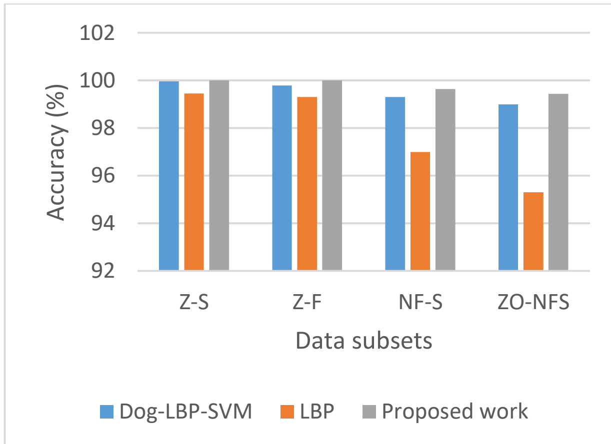

Fig. 7. Performance comparisons with existing works.

4. CONCLUSION

In this paper, an epilepsy seizures detecting method with improved detection accuracy is developed. For that discrete stationary wavelet transform based Stockwell transform is proposed which works under a discrete wavelet transform with discrete Fourier transform. Then the feature extraction is carried out with spectral and temporal features and find the peak of the sub-bands with amplitude distribution estimation for EEG signals. The feature selection is processed by a modified filter bank based particle swarm optimization. To limit the computational time, K nearest neighbour based SVM classifier is used. Finally, the classifier will segregate the EEG signals into normal, Ictal and inter ictal. The performance was validated by classification problem under different classes. From the results, it is concluded that the proposed work performance leads over other existing works.

NOMENCLATURES

$\psi_{j,k}(t)$	Mother Wavelet
$S(t,f)$	stationary ST
$x(t)$	Input signal in time series
App	Approximation Coefficient
Det	Detail Coefficient
zcr	Zero crossing rate
E_T	Short Term Energy
X	Discrete Fourier Transform
PSD	Power Spectral Density

Δf	Frequency Interval
W	Window function
Greek Symbol	
ε	Decimated Discrete Wavelet Transform
Subscripts	
j	Scale parameter
k	Shift parameter
swt	Stationary Wavelet Transform
fea	feature

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