A novel peak signal feature segmentation process for epileptic seizure detection

Abstract Epilepsy is a brain disease in nerves which causes sudden seizure, sensations, and once in a while loss of mindfulness. This disorder is difficult to find manually because of its unpredictable nature since it is very hard to treat. The World Health Organization states that fifty million people having this type of disorder worldwide. Automatic detection assumes a significant role in the finding of epilepsy for it can get imperceptible data of Epileptic Electroencephalogram Signals precisely and diminish the burdens of medical field. The Brain's function is monitored by using these EEG signals electrically. The goal of this paper is to find a classification on Electroencephalogram (EEG) signals using the Bonn University datasets. In order to address this challenge, we propose a new Peak Signal Features (PSF) method which extracts high and low peak features from EEG signals. In addition, Support Vector Machine, Decision Tree and K-Nearest Neighbor are used for classification. Finally, overall accuracy and the Mean Square Error rates of the above three classification methods with proposed method are measured. The experimental result demonstrates the effectiveness of the proposed approach. It also proves that SVM with proposed Peak Signal Features method gives better result than the other methods.

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Keywords Butter worth filter · Classification · Decision tree · Electroencephalogram · Entropy · Epilepsy · K-nearest neighbor · Machine learning · Support vector machine

Abbreviations

PSF	Peak signal features
SVM	Support vector machine
DT	Decision tree
KNN	K-nearest neighbor
ESD	Epileptic seizure detection

1 Introduction

Epilepsy is one of the challenging diseases which causes recurrent seizures and reoccur repeatedly. Imbalanced electrical change of the EEG signal may indicate abnormal by the electrodes which are placed on the scalp to record the brain activity. Abnormalities in these signals represent brain diseases like dementia, mental disorder, epilepsy, stroke, etc. [1]. By using these signals, epilepsy can be found out easily. Finding this type of disease on EEG signals manually is a tedious one and it takes time. Automated systems are used to detect normal and abnormal patterns easily.

The proposed Peak Signal Features (PSF) extracts the high and low peak signal features. Butter worth filter is used to remove noise from the input EEG signal. Segmentation performance selects high peak and low peak signal both horizontally and vertically. Adaptive threshold method is used for high and low peak signal selection and the features are extracted by entropy. The proposed PSF method extracts the most robust features. The output of this

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method is fed into the three classifiers to classify the normal and abnormal state of the EEG signal.

Supervised learning methods are used to model and predict categorical variables. Support Vector Machine calculates the distance between two observations by a mechanism called kernels and finds the decision boundary which maximizes the distance between closest members of separate classes. It can also work for non-linear decision boundaries and it is strong against over fitting particularly for high dimensional space. SVM concentrate on memory and it takes care of choosing the right kernel. It is not good for the larger datasets. Decision Tree is based on decision making process by doing test on each point. Classification based on class labels and regression depends on continuous numerical values. The KNN classification is performed by calculating distance between data values. In this paper, Classification is performed on the EEG signals by using the Machine Learning algorithms SVM, DT, and KNN respectively. Hence the performance of SVM, DT, and KNN is found by using the training Peak Signal Features and testing sample. The accuracy of training, the prediction of testing, and the mean square error rates are also tabulated. The main contribution of this paper is to detect Epileptic Seizure disease using EEG signals in a faster time with minimum error rates.

The rest of this paper is arranged as follows: Sect. 2 provides a survey of related works in the areas of epileptic seizure detection, feature extraction and classification. Section 3 depicts the framework of the proposed methodology PSF and also explains the preprocessing, and segmentation, feature extraction and the classification with the above said three algorithms. Section 4 details the results obtained from this proposed work and provides relevant discussions on them. Section 5 gives conclusions and future works for this system.

2 Related work

Various works have been carried out towards feature selection and classification for EEG signals in the past by different researchers. Among them, Lin et al. [2] proposed a method to recognize emotional responses using EEG signals. They investigate the relationship between EEG and music-induced emotion responses, in three factors such as features types, temporal resolutions and the components of EEG. Brain functions related to emotional activities were shown as a result particularly for an alpha, theta, and delta component bands. 60 features were obtained by EEG components and the accuracy of this method was 92.73%. However, the robust features cannot be found in this method and it contains some features repeatedly and also changes with user activity.

Bayram et al. [3] classified EEG signals by Support Vector Machine to decide whether the task to be performed or not. Their experimental result shows that RBF was 71.43%, SFS was 72.53% and the best one was SBE that is 74.73% with eleven features. However, the top and middle section of the bandwidth should need to be analyzed.

Ishfaque et al. [4] reduces the dimensionality of the data by Principle Component Analysis and further classified by ANN, LDA, and DT which finally concluded as ANN with accuracy 81.6% as the best one compared to LDA and DT. Guangyi Chen [5] proposed a dual-tree complex wavelet (DTCWT)—fourier features and performs only upto 5 scales and conducts with FFT 4th and 5th scales. Replacing FFT with sparse FFT works even faster. Acharya et al. [6] used various entropies like REN, SampEn, SEN, PE, FE, TE, ApEn, WE, RQAEn, S1, S2, PhEn, and KSE to find the normal and abnormal signal and the results were tabulated as per ranking. They conclude that RE, SampEn, SEN, and PE are optimal to differentiate features for proper classification.

Wang et al. [7] introduced a detection framework and compared decision tree algorithm C4.5, the random forest (RF), the support vector machine (SVM) based decision tree (SVM + C4.5), and SVM based RF (SVM + RF) to two-group, three-group and five-group classification. However, the performance of rules should be improved with the lesser one by maintaining the accuracy of a result. Gehlot et al. [8] proposed Empirical Mode Decomposition (EMD) method for differentiating the EEG signals as focal and non-focal into narrow-band amplitude and frequency modulated (AM–FM) called intrinsic mode functions (IMFS). The output was displayed as a 3D phase with the help of phase space reconstruction (PSR) and the average mean of Euclidean distance (AMED) and average standard deviation of Euclidean distance (ASED) yields good results. Finally, Kruskal-walls were applied to the extracted features for quantization. However, combining AMED and ASED with optimum classification technique may have higher accuracy.

Siuly, Li [9] designed a robust feature extraction optimum allocation based principal component analysis method (OA-PCA). Dimensionality reduction was made and construction of uncorrelated components principal component analysis (PCA) was used. OA-PCA feature set was then classified using LS-SVM, NB, KNN and LDA methods. LS-SVM-IVI finally attained 100% and improvement was 10%. The further process should going to be done on real-time applications in a multi-class type.

Oliva et al. [10] presented an application of cross-correlation technique, and KNN and the output were fed into tenfold cross-validation. KNN K = 1 and K = 7 show good output in a contingency table. The CCo and other optimal features extraction techniques will be found and would be applied to other medical decision-making processes.

Guzel Aydin [11] used emotion recognition ''db5'' wavelet-based for extracting some important features like happy, melancholy & disgust on both frequency bands and text with graphics-based language. However, to create a link with emotional states, some other wavelet method should be analyzed for improvement. Lin et al. [12] proposed a stacked sparse auto-encoder (SSAE) which extracts the high-level features which were fed into soft-max classifier and yield the best of 96% as result. However, improvement needs on both theory and practical side for deep spatiotemporal auto-encoder for extracting more features.

Riaz et al. [13] introduced EMD empirical mode decomposition as a time–frequency analysis that gave intrinsic mode functions (IMF) for decomposition. They used SVM as a classifier to classify normal or epilepsy signal. Some most vital should need to be extracted to enhance the accuracy for both cases and even have to form an equipment for that method.

Zhang et al. [14] applied time–frequency analytical algorithm, local mean decomposition (LMD) to decompose into different product functions (PFs). Features of each PF are the input for classification with the algorithm back propagation neural network (BPNN). K-nearest neighbor (KNN), Linear discriminant analysis (LDA) un-optimized SVM and SVM optimized by genetic algorithm (GA-SVM). However, improved studying about the varying of class and application of this method to another difficult dataset are also needed.

Jaiswal et al. [15] introduced Local Centroid Pattern (LCP) and one-dimensional local ternary pattern (1D-LTP) for finding information features. Vector-histograms and its application to machine learning classifiers yields better results than the existing methods.

Oliva et al. [16] used Cross-correlation (CC) method for feature extraction. Instead of selecting the feature randomly a reference is made by a method called CC with artificial reference (CCAR) and classified using J48, 1NN, NB, BP-MLP, and SMO. However, it is not applied to other EEG signals and diseases. Other techniques will be needed to extract features by using different classification machine learning methods.

Prabhakar and Rajaguru [17] obtained variance, covariance, events, energy, sharp waves, spike waves, and peaks parameters from the EEG signal and classified using Expectation–Maximization (EM) and modified Expectation–Maximization (MEM) algorithm. Another heuristic method has got to be applied with different machine learning classifiers to classify and for detecting the disease. Sohail et al. [18] reviewed a paper about Data Mining techniques for the growth of Medical data. Methods like SVM, Naïve Bayes, Decision Tree, KNN, etc. were used for the disease like heart disease, breast cancer, skin cancer, lung cancer, diabetes and hands-on performance were collected and tabulated. However, Hybrid techniques were needed to be developed for better performance.

Rajaguru and Prabhakar [19] used morphological filtering and LDA (Linear Discriminant Analysis), Log LDA (L-LDA) and Kernel LDA (K-LDA) classifiers for classification. They obtained an average accuracy of LDA-97.39%, LLDA 96.87%, and K-LDA 96.45%. However, further improvement should be needed by changing the morphological filtering and also different classification methods to enhance the performance.

Abdelhameed et al. [20] proposed one-dimensional deep convolutional auto-encoder and three neural network system classifiers. They yield 100% accuracy for each system by using Bi-LSTM as 99.33% average accuracy. The advantage of the proposed work was Bi LSTM performed on raw input. Qiu et al. [21] applied Denoising Sparse Auto Encoder (DSAE) for best feature selection where sparsity extracted on the hidden layer. They externally added noise for better results.

Sun et al. [22] used Echo State Network (ESN) for encoding and decoding and FE-ESN feature extraction. They performed clustering and yield better results. Different channels were used for spatiotemporal auto-encoder and applied on different classification algorithms for finding various sorts of diseases using EEG signals.

Attia et al. [23] developed an extraction method by applying recurrent auto encoders on multivariate EEG signals. Autoregressive (AR) and firefly optimization (FA) were applied which gave the best model order (P) with minimum residual variance. However, combining different AR methods with ARIMA for extracting the features improves the accuracy.

Tuncer et al. [24] presented a novel texture descriptor for distinctive feature extraction. They used component analysis SVM, KNN, Quadratic discriminant analysis, and linear discriminant analysis for classifications which yields 93.0% result. However, this work cannot be applied on ECG, EMG and other signals. The replacement method with combining LSP technique has also need to be developed.

Sharmila and Geethanjali [25] used Time-domain (TD) features like waveform length (WL), number of zero-crossing (ZC) and the number of slope sign changes (SSC) obtained directly from DWT and EEG data. However, it should be applied to real-time systems and pattern recognition in medical field.

3 Methodology

3.1 Peak signal feature (PSF)

The proposed work comprises of the accompanying parts to be specific preprocessing, segmentation, feature extraction, and classification. The framework of the proposed system is depicted in Fig. 1.

3.2 Input EEG signal

EEG signals are essentially used for finding brain diseases. In this work, Bonn university dataset of EEG signals are collected for detecting epileptic seizure. The dataset contains two healthy volunteers and three patients' signals. It is used for the investigation of finding normality or abnormality of the signal.

3.3 Preprocessing

In this proposed work, 5 datasets are used for analyzing PSF method. The collected data is first given to preprocessing module, where the preprocessing takes place. This section presents basics about the artifact removal of epileptic seizure detection using the butter worth filter. The following Eq. 1 is used for calculating the Butter worth filter,

$$H_{(jx)} = \frac{1}{\sqrt{1 + e^2 \left(\frac{x}{x_p}\right)^{2n}}} \tag{1}$$

where, n—Filter order, x—Omega (2gf), e—Epsilon (Maximum pass band gain).

The sub-bands of the frequency are extracted by the Butterworth band-pass filter and if it is high pass then it will remove artifacts from the low frequency [26, 27]. Noise and disturbance from the outside such as blinking of eyes, movements of muscles are cleaned by using these filters [28]. This filter flats the sharp points maximally and it is utilized in control systems. There are two bands such as pass band and stop band which contains no ripple effects. This filter is the most commonly used one because of its responsiveness of frequency is acceptable.

The output of preprocessing is demonstrated in Fig. 2. It shows how the raw input EEG signals were converted after artifacts removal using Butterworth filter.

3.4 Segmentation

After preprocessing the raw input signal, adaptive threshold method is applied for segmenting those EEG signals. It is based on threshold value for each point depending upon the closest point in small area because each area have different threshold. It is segmented for feature extractions which are above the fixed point (i.e.) a threshold. The signal boundary limit is based on threshold value.

Figure 3 depicts the proposed method; how the high and low peak signal selection is performed based on threshold value. It clearly represents the selection of high and low peak area on the EEG signal which is used for feature extraction and fed into training. This experiment is done for the whole five datasets.

This equation contains mean and the median otherwise,

$$Threshold = \frac{minimum + maximum}{2} \tag{2}$$

The above Eq. (2) is used for calculating adaptive threshold value.

3.4.1 *Horizontal segmentation*

In our proposed work, each file in a dataset is horizontally segmented for finding high peak and low peak signal based on the adaptive threshold value. The Features above the

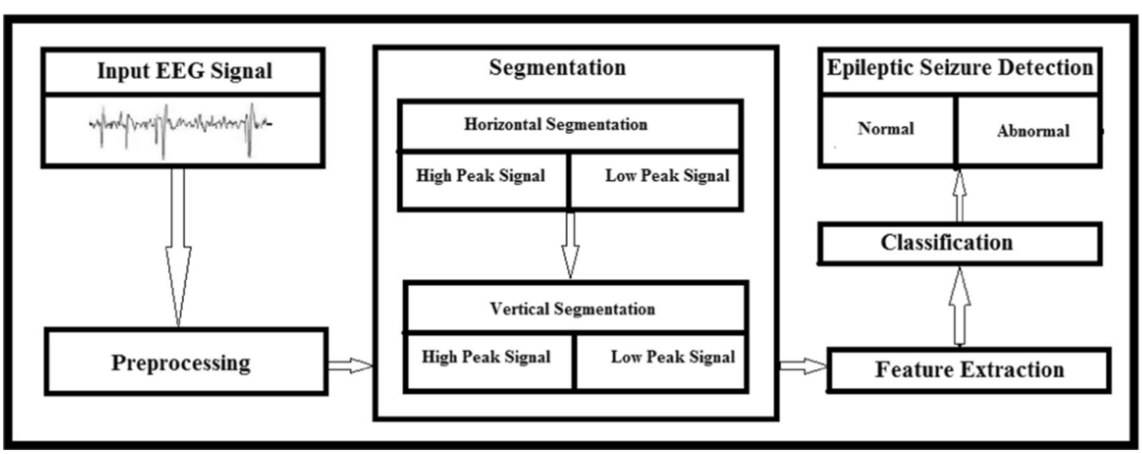

Fig. 1 Proposed PSF based ESD Framework

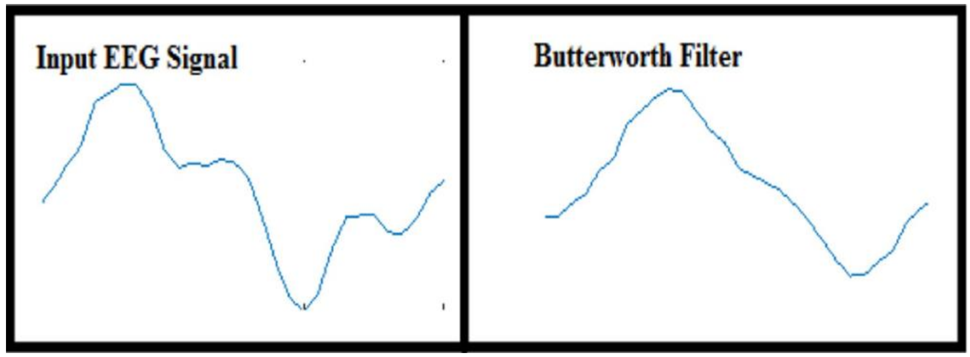

Fig. 2 Pre-processing of input EEG signal

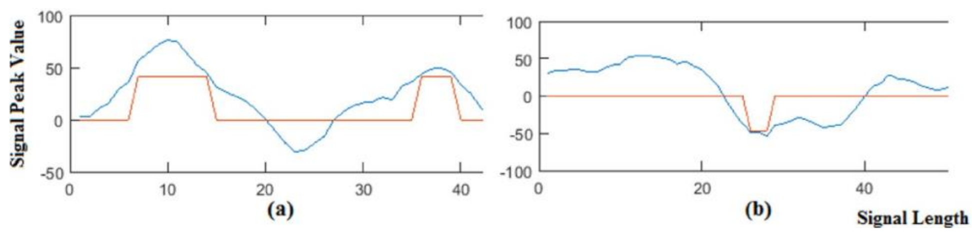

Fig. 3 a High peak b low peak signal selection

threshold values are selected and extracted for classification. The features selected above the threshold up to the maximum level are called the high peak signals whereas the features selected below the threshold up to the minimum level called low peak signals. The above Fig. 4 depicts horizontal segmentation of the EEG signal.

3.4.2 Vertical segmentation

Each segment is having some features based on the number of vertical segmentation. So the horizontal segmented frame is divided into four regions. Each region is having one feature extracted by entropy. Therefore four features will be extracted for high peak signals whereas low peak signals are also extracted from each file. From a total of 4 datasets, one dataset contains hundred files. So, four hundred features are extracted for each dataset. Totally, 2000 (400 9 5) features are extracted from five data sets. Likewise, low peak signals will also have 2000 features. The above Fig. 5 depicts vertical segmentation of the EEG signal.

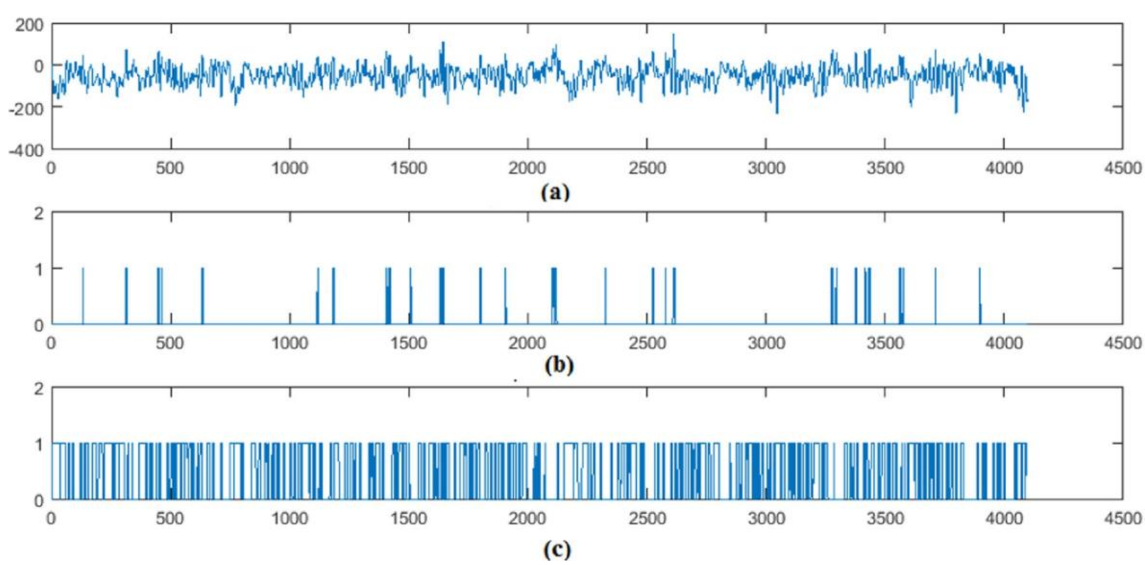

Fig. 4 Horizontal segmentation: a input signal b high peak c low peak selection

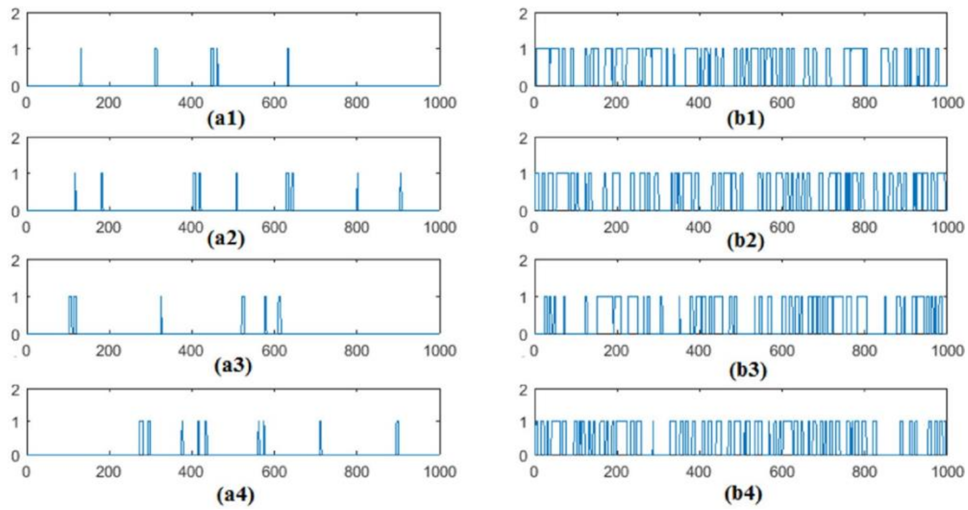

Fig. 5 Vertical segmentation: a1–a4 high peak b1–b4 low peak selection

3.5 Feature extraction

3.5.1 *Entropy*

Entropy is applied in thermodynamics, finance, probability-based applications, astrophysics and life sciences [29]. EEG signals normally have complexity and these signals are measured by entropy. This work used entropy for feature extraction so that the changing parameters without the linearity and time-series variance can be accessed. The optimized features are extracted using this entropy method and further fed as an input for classification. It can be calculated using the Eqs. (3) and (4) as follows:

$$e(p1, p2, \ldots pn) = -\mathrm{p}_1 \log p_1 - p_2 \log p_{2\ldots\ldots} - p_n \log p_n \quad (3)$$

$$E(X) = -\sum_x p(x) \log p(x) \quad (4)$$

where, E(X) is the Entropy of X.

It is based on the measurement of probability for uncertain values.

3.6 Classification

Different classification strategies have been used to characterize EEG dataset into an epileptic seizure and non-epileptic seizure classifications. So as to register the association among extracted features and seriousness towards the target conditions, the from now on classifiers are utilized in this study. Machine Learning algorithms such as SVM, DT and K-Nearest Neighbor algorithms are used to classify EEG signals.

SVM is a supervised machine learning algorithm which is used to perform classification and Regression. It works clearly well and effective in classifying EEG signals. Accuracy of prediction should be maximized by using the optimization technique which avoids over fitting of training data automatically. In kernel space, input data builds a linear model [30].

In 1984 Breiman et al. [31] suggested Classification and Regression Tree (CART) which develops binary trees called Hierarchical Optimal Discriminate Analysis (HODA). It infers that node in a decision tree splits into two groups. It used Gini Index for attribute selection. The highest reduction is selected for splitting which is used for further process and cost complexity was used. The prediction can be done by regression between the predictor variable and time [32].

Both classification and regression problem use this K-nearest neighbor method. A new data point is placed based on the similarity of the features which have the nearest relationship. Distance is calculated between the data points by using any one of the methods like the Manhattan, the Euclidian or the Hamming distance [33].

3.7 ESD (Epileptic seizure detection)

This is the final process of the proposed methodology. It can detect the input EEG signal as epileptic seizure and non-epileptic seizure. The proposed method detects the epilepsy optimally after extracting the best features from the input EEG signal and it can be used for automatic seizure detection. The abnormality in the brain that causes epileptic seizure can be easily found using our proposed method.

4 Results and discussion

The experimental analysis is carried out with the Bonn university dataset for accessing the proposed system by directing different experiments. The dataset contains two healthy person signals and three epileptic patients' signals. It is named as A, B, C, D and E and each have 100 single-channel signals. The first two A and B are the signals of healthy person with eyes open and closed. The other three are the epileptic patients signal and E captured during epileptic zone where C, D captured before surgery [34]. These datasets are used for testing.

The performance of the classification is analyzed using the accuracy. The Eq. (5) is used for the above criteria where TP is a positive and TN is the negative class of samples that are correctly classified. Likewise, FP and FN are positive and negative class of samples that are incorrectly classified. The equation used to find the accuracy is given as,

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{5}$$

The overall performance accuracy of the normality and abnormality of signals for the above said datasets and algorithms are shown in Table 1.

Healthy signal A is paired with unhealthy signals C, D and E for predicting performance in pair wise dataset. Likewise, another healthy signal B is paired with unhealthy signals C, D and E. Table 2 shows the accuracy of dataset pair for the three algorithms SVM, DT, and KNN with PSF.

The error rate for three algorithms SVM, DT, and KNN for dataset pair is shown in Table 3.

Figure 6 depicts the error rate for five datasets A, B, C, D, and E. The proposed method PSF with SVM classification gives less error rate for the dataset E. The DT method with PSF gives the next level reduced error rate. It also gives the minimum error rate for dataset E.

Figure 7 represents the prediction performance of the five datasets. It shows that the dataset E have more accurate prediction by the proposed method PSF with SVM other than four datasets A, B, C, D and two methods DT and KNN. The DT algorithm gives better results next to the SVM.

The overall performance accuracy of the classification techniques such as SVM, KNN and DT algorithms with PSF for the five datasets are shown in Table 4.

Table 1 Overall performance of the normal and abnormal signal

Algorithms	Accuracy%		Error Rate	
	Normal	Abnormal	Normal	Abnormal
PSF + SVM	95.56	96.54	0.044	0.035
PSF + KNN	44.63	40.92	0.554	0.591
PSF + DT	93.55	94.77	0.064	0.052

Table 2 Prediction performance in pair wise dataset

Dataset pair	PSF + SVM%	PSF + DT%	PSF + KNN%
Dataset A & C	95.06	92.71	45.75
Dataset A & D	96.06	93.73	46.00
Dataset A & E	96.94	95.21	40.31
Dataset B & C	94.63	92.43	44.38
Dataset B & D	96.63	94.46	44.88
Dataset B & E	98.38	97.43	33.50

Table 3 Error rate measure in pair wise dataset

Dataset pair	PSF + KNN%	PSF + DT%	PSF + SVM%
Dataset A & C	0.56	0.08	0.05
Dataset A & D	0.55	0.06	0.03
Dataset A & E	0.67	0.03	0.02
Dataset B & C	0.56	0.08	0.05
Dataset B & D	0.55	0.06	0.03
Dataset B & E	0.67	0.03	0.02

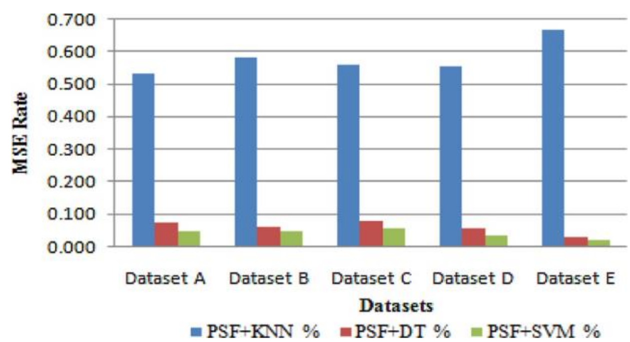

Fig. 6 Error rates for PSF + KNN, PSF + DT and PSF + SVM

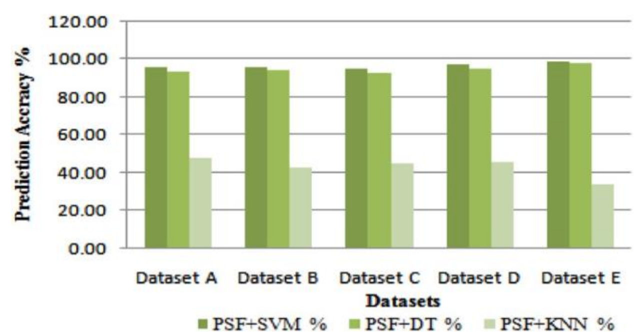

Fig. 7 Prediction performance of PSF + KNN, PSF + DT and PSF + SVM

Table 4 Overall performance

Algorithms	Accuracy%	Error Rate
PSF + SVM	99.60	0.039
PSF + KNN	42.40	0.576
PSF + DT	94.29	0.057

It displays the proposed method gives 99.60% accuracy and 0.039 as the reduced error rate for SVM with PSF method.

5 Conclusion and future works

Countries like China reach a dead line in affecting the diseases like epileptic seizure. In this paper, a novel Peak Signal Features (PSF) method has been proposed for extracting high peak and low peak signals for efficient epileptic seizure detection. From PSF, epilepsy is easily identified using EEG signals in a minimal time. The proposed system has been tested with Bonn university dataset and the method shows 99.60% accuracy for SVM, 42.40% for KNN and 94.29% for DT. From the experiments conducted, it is proved that the proposed model provides better detection with 99.60% accuracy using SVM classifier and corresponding error rate which displays minimum value. Thus the proposed PSF method can be used in the real time environment for automatic epileptic seizure detection. Future works in this direction, is the use of another datasets of EEG signals for enhancing the performance and identifying different type of brain diseases using this method.

References

1. Alkan A, Kiymik MK (2006) Comparison of AR and Welch methods in epileptic seizure detection. J Med Syst 30:413–419. https://doi.org/10.1007/s10916-005-9001-0
2. Lin Y, Wang C, Wu T, Jeng S, Chen J (2008) Support vector machine for EEG signal classification during listening to emotional music. 2008 IEEE 10th Workshop on Multimedia Signal Processing, Cairns, Qld, pp. 127–130
3. Bayram KS, Kızrak MA, Bolat B (2013) Classification of EEG signals by using support vector machines. 2013 IEEE INISTA, Albena, pp. 1–3
4. Ishfaque A, Awan AJ, Rashid N, Iqbal J (2013) Evaluation of ANN, LDA and decision trees for EEG based Brain Computer Interface. 2013 IEEE 9th International Conference on Emerging Technologies (ICET), Islamabad, pp. 1–6
5. Guangyi C (2014) Automatic EEG seizure detection using dual-tree complex wavelet-Fourier features. Expert Syst Appl 41(2014):2391–2394. https://doi.org/10.1016/j.eswa.2013.09.037
6. Acharya UR, Fujita H, Sudarshan VK, Bhat S, Koh JEW (2015) Application ofentropies for automated diagnosis of epilepsy using EEG signals: a review. Knowl Base Syst 88:85–96
7. Wang G, Deng Z, Choi KS (2015) Detection of epileptic seizures in EEG signals with rule-based interpretation by random forest approach. In: Huang DS, Han K (eds) Advanced intelligent computing theories and applications. ICIC 2015. Lecture Notes in Computer Science, vol 9227. Springer, Cham
8. Gehlot M, Kumar Y, Meena H, Bajaj V, Kumar A (2015) EMD based features for discrimination of focal and non-focal EEG signals. In: Mandal J, Satapathy S, Kumar Sanyal M, Sarkar P, Mukhopadhyay A (eds) Information systems design and intelligent applications. Advances in intelligent systems and computing, vol 340. Springer, New Delhi
9. Siuly S, Li Y (2015) Designing a robust feature extraction method based on optimum allocation and principal component analysis for epileptic EEG signal classification. Comput Methods Programs Biomed 119:29–42
10. Oliva J, Rosa J (2016) Differentiation between normal and epileptic EEG using K-nearest-neighbors technique. https://doi.org/10.1007/978-3-319-50478-0_7.
11. Guzel Aydin S, Kaya T, Guler H (2016) Wavelet-based study of valence–arousal model of emotions on EEG signals with LabVIEW. Brain Inf. 3:109–117. https://doi.org/10.1007/s40708-016-0031-9
12. Lin Q et al (2016) Classification of epileptic EEG signals with stacked sparse autoencoder based on deep learning. In: Huang DS, Han K, Hussain A (eds) Intelligent computing methodologies. ICIC 2016. Lecture Notes in Computer Science, vol 9773. Springer, Cham
13. Riaz F, Hassan A, Rehman S, Niazi IK, Dremstrup K (2016) EMD-based temporal and spectral features for the classification of EEG signals using supervised learning. IEEE Trans Neural Syst Rehabil Eng 24(1):28–35
14. Zhang Y, Ji X, Liu B et al (2017) Combined feature extraction method for classification of EEG signals. Neural Comput Appl 28:3153–3161. https://doi.org/10.1007/s00521-016-2230-y
15. Jaiswal AK, Banka H (2018) Epileptic seizure detection in EEG signal using machine learning techniques. Australas Phys Eng Sci Med 41:81–94. https://doi.org/10.1007/s13246-017-0610-y
16. Oliva JT, Garcia Rosa JL (2017) How an epileptic EEG segment, used as reference, can influence a cross-correlation classifier? Appl Intell 47:178–196. https://doi.org/10.1007/s10489-016-0891-y
17. Prabhakar SK, Rajaguru H (2018) Comparison of fuzzy output optimization with expectation maximization algorithm and its modification for epilepsy classification. In: Guru D, Vasudev T, Chethan H, Kumar Y (eds) Proceedings of international conference on cognition and recognition. Lecture notes in networks and systems, vol 14. Springer, Singapore
18. Sohail MN, Jiadong R, Uba MM, Irshad M (2019) A comprehensive looks at data mining techniques contributing to medical data growth: a survey of researcher reviews. In: Patnaik S, Jain V (eds) Recent developments in intelligent computing, communication and devices. Advances in intelligent systems and computing, vol 752. Springer, Singapore
19. Rajaguru H, Prabhakar SK (2018) Application of morphological filtering with modifications in linear discriminant analysis classifier for epilepsy classification from EEG signals. In: Hemanth D, Smys S (eds) Computational vision and bio inspired computing. Lecture notes in computational vision and biomechanics, vol 28. Springer, Cham
20. Abdelhameed AM, Daoud HG, Bayoumi M (2018) Epileptic seizure detection using deep convolutional autoencoder. 2018 IEEE international workshop on signal processing systems (SiPS), Cape Town, pp. 223–228

21. Qiu Y, Zhou W, Yu N, Du P (2018) Denoising sparse autoencoder-based ictal EEG classification. IEEE Trans Neural Syst Rehabil Eng 26(9):1717–1726
22. Sun L, Jin B, Yang H, Tong J, Liu C, Xiong H (2019) Unsupervised eeg feature extraction based on echo state network. Inf Sci 475:1–17
23. Attia A, Moussaoui A, Chahir Y (2019) Epileptic seizures identification with autoregressive model and firefly optimization based classification. Evol Syst. https://doi.org/10.1007/s12530-019-09319-z
24. Tuncer T, Dogan S, Akbal E (2019) A novel local senary pattern based epilepsy diagnosis system using EEG signals. Australas Phys Eng Sci Med 42:939–948. https://doi.org/10.1007/s13246-019-00794-x
25. Sharmila A, Geethanjali P (2019) Evaluation of time domain features on detection of epileptic seizure from EEG signals. Health Technol. https://doi.org/10.1007/s12553-019-00363-y
26. Anupallavi S, MohanBabu G (2020) A novel approach based on BSPCI for quantifying functional connectivity pattern of the brain's region for the classification of epileptic seizure. J Ambient Intell Human Comput. https://doi.org/10.1007/s12652-020-01774-w
27. Ghassemi N, Shoeibi A, Rouhani M, Hosseini-Nejad H (2019) Epileptic seizures detection in EEG signals using TQWT and ensemble learning. 2019 9th International conference on computer and knowledge engineering (ICCKE), Mashhad, Iran, pp. 403–408
28. Lopetegui E, Zapirain BG, Mendez A (2011) Tennis computer game with brain control using EEG signals. 2011 16th International conference on computer games (CGAMES), Louisville, KY, pp. 228–234
29. Li F, Fan Y, Zhang X et al (2020) Multi-feature fusion method based on EEG Signal and its application in stroke classification. J Med Syst 44:39. https://doi.org/10.1007/s10916-019-1517-9
30. Richhariya B, Tanveer M (2018) EEG signal classification using universum support vector machine. Expert Syst Appl. https://doi.org/10.1016/j.eswa.2018.03.053
31. L. Breiman, J. Friedman, C. J. Stone, and R. A. Olshen, Classification and regression trees. CRC press, 1984.
32. Bhumika G, Aditya R, Akshay J, Arpit A, Naresh D (2017) Analysis of various decision tree algorithm for classification in data mining. Int J Comput Appl 163(8):15–19
33. Rivero D, Fernandez-Blanco E, Dorado J, Pazos A (2011) A new signal classification technique by means of Genetic Algorithms and kNN. 2011 IEEE Congress of Evolutionary Computation (CEC), New Orleans, LA, pp. 581–586
34. EEG Time Series (Epileptic Data) November (2005). http://www.meb.unibonn.de/epileptologie/science/physik/eegdata.html