A Novel LBP-Based Algorithm for Automatic Diagnosis of Epileptic Seizures

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A NOVEL LBP-BASED ALGORITHM FOR AUTOMATIC DIAGNOSIS OF EPILEPTIC SEIZURES

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***Abstract*— Epilepsy is a condition of brain dysfunction which affects about 1% of the population across the globe. Diagnosing seizures is an unavoidable component in its treatment and control. Epilepsy detection is commonly done using electroencephalogram (EEG) signals. A new EEG based methodology for automatic diagnosis of epileptic seizure has been proposed in the present work. Local Binary Pattern (LBP) values were computed on the preprocessed EEG signal and the morphological significance of LBP values were analyzed, from which eight significant LBP values were selected, whose histogram per each epoch was considered as features. This algorithm was tested for its performance on CHB-MIT EEG database for three different classifiers, namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Linear Discriminant Analysis (LDA). Among the three classifiers, K-NN shows better performance with 100% Sensitivity and 0.52/h false detection rate (FDR). These values point to the superiority of the present approach over the existing approaches for automatic diagnosis of epilepsy.**

***Keywords*—Electroencephalogram, Local Binary Pattern, Support Vector Machine, K-Nearest Neighbor, Linear Discriminant Analysis.**

I. INTRODUCTION

EPILEPSY, a disease known from ancient times, is a symptom of paroxysmal and abnormal discharges in the brain. Epilepsy is considered as the second most commonly occurring disease. It is generally characterized by the transient disturbances of brain functions leading to loss of mindfulness, undetectable defects in the movement pattern, very mild twisting of muscles, and disturbances visual, auditory, gustatory senses and mood; many others are often beyond manual recognition [1]. Epilepsy affects approximately 70 million people of all age groups globally, in which only 70% are curable by any form of drugs [2]. People with epilepsy have to bear recurrent seizures at random times, which usually take place without any warning. According to the World Health Organization (WHO), epilepsy is differentiated by repeated seizures, which are responses to unexpected and usually short-term electrical discharges in a group of brain cells. Researches target in the direction of epilepsy control program since timely detection of seizures can inarguably prevent death and neurodevelopmental delay of neonates [3].

Electroencephalography (EEG) is a globally accepted and applied technique to detect abnormalities in the signals in the brain [4]–[9]. Epilepsy is random in nature. Hence, visual inspection of EEG signals can be tiring and time-consuming. The availability of trained neurologists in the field of neurology is too limited in countries like India, which fall under the 'developing countries' category. That being said, it is to be noted that even trained neurologists find it difficult to detect seizures because of the existence of ocular and musculature artefacts. This scenario has resulted in the emergence of computer-based detection and analysis of EEG signals.

The analysis of EEG signals with the aim of automatic epileptic seizure detection has become an significant area of research, especially in the past few eras [10]. Mostly, a wide variety of algorithms have been proposed for analyzing epilepsy using the EEG signals obtained. These include the time [11]–[14], the frequency [15]–[17], and time-frequency domains analysis [18]–[22].

Prior et al. [23] came up with an idea to use cerebral function monitor. Epilepsy were identified as an immense rise in EEG amplitude, which is then followed by a noticeable decrease and by hefty EMG activity. An electronic circuit that could identify seizures was proposed by Babb et al. [24]. The circuit identifies seizures through a swift progression of large amplitude spikes. The nonlinear dynamics of a signal was studied by Sharma et.al. [25]. The 2D and 3D phase space representations (PSRs) of intrinsic mode functions (IMFs) derived from empirical mode decomposition (EMD) of EEG signals was utilized for the classification of epileptic seizure and seizure-free EEG signals. But the bigger extent of computational time was reduced by Paul et al. [26] who considered phase correlation to capture the motion information between the current and reference blocks, and invented an algorithm for direct motion estimation mode prediction. Tzallas et al. [27] compared non stationary properties of EEG signals by using Short-time Fourier transform (STFT) and several t-f distributions (TFDs), and these properties were used to calculate the power spectrum density (PSD) for each segment. Artificial neural network (ANN) classifier makes use of these features for the diagnosis of epilepsy. Najmah et al. [28] discussed a patient specific det-

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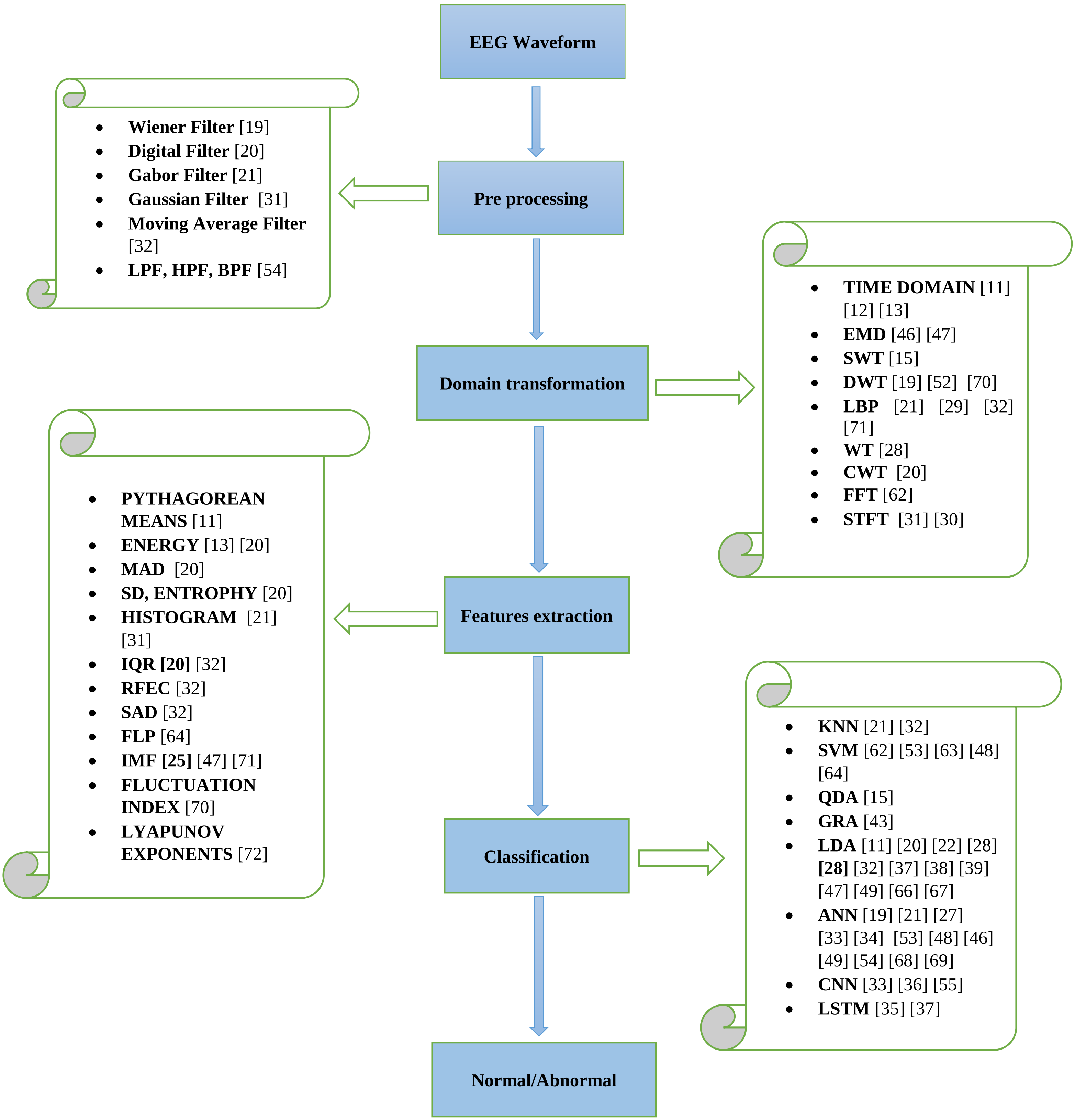


Fig.1. Summary of Literature Review

ection system, where discrete wavelet transform (DWT) was applied on scalp EEG data. The mean and variance of ictal and inter-ictal data were fed to linear classifier. Satisfactory results of 98.3% specificity, 96.06 % sensitivity and 97.19 % accuracy were achieved when tested on database collected from Boston Children's Hospital [29].

Local binary pattern (LBP) is yet another factor that has been considered and suggested for the classification of epileptic seizure EEG signals [30]. Tiwari et al [31] calculated the LBP of the EEG signals fragmented by making use of Gabor filter bank and then suggested nearest neighbor classifier for detection of epilepsy. Shanir et al. [32] proposed a set of novel LBP based morphological features like rising and falling edge count (RFEC) and sum of absolute differences (SAD) for each epoch. The discriminating strength of these features when combined with interquartile range (IQR) provided satisfactory result using KNN classifier with a mean accuracy of 99.7% when tested on CHB-MIT database.

Deep learning is one of the new techniques that has risen in recent times. Acharya et al. [33] was the first to employ a 13-layer deep convolutional neural network (CNN) algorithm for automated classification of normal, pre-ictal, and seizure classes. This technique achieved accuracy, specificity, and sensitivity of 88.67%, 90.00% and 95.00% respectively when tested on database collected from Bonn University, Germany [4]. Elman Network (EN), a recurrent neural network was employed by Srinivasan et al. [34] for detecting epilepsy. Five different elements, two-time domain and three-frequency domain features were used, and accuracy of 99.6% was achieved. Ahmedt-Aristizabal et al. [35] tried out the hypothesis that spatio-temporal traits of the patient's response and behavior obtained from the videos recorded can discriminate between the mesial temporal from extra temporal seizures using deep learning approaches like CNN and long short-term memory (LSTM). Daoud et al. [36] computed Mean Power Frequency (MPF) from the generated IMFs so as to condense the dimension of feature vectors for firm classification using Multilayer Perceptron (MLP). Also, CNN was used as classifier for multiclass classification task to obtain high classification accuracy and robustness. Hussein et al. [37] introduced another deep learning-based approach which spontaneously studies the discriminative features of epileptic seizures. EEG segments containing normal artifacts were deleted and those with delicate ones were de-noised using a band-pass filter. LSTM networks is used to study the high-level representations of the normal and the seizure EEG patterns.

Many algorithms for automatic seizure detection with different feature classifier combination is proposed recently have a problem lower performance or/and computational cost. A summary of recent work is shown in Fig. 1. Present work aims to find better performing algorithm with lesser computation. This paper analyzed morphology behind each LBP code and selected morphologically significant 8 LBP codes. Histogram of these selected LBP codes are used as a feature. The proposed algorithm has been tested on 124 seizures from 21 patients from CHB-MIT (Children's Hospital Boston–Massachusetts Institute of Technology) continuous EEG database for three different classifiers namely KNN, LDA and SVM. A new feature classifier combination set has been put forward, which played a pivotal role in the diagnosis of epileptic seizure and have achieved significant result in the diagnosis of seizures.

II. LOCAL BINARY PATTERN

LBP is a gray-scale invariant texture measure [38] [39]. LBP operator is derived from a general definition of facial expression in a local neighborhood. LBP, is an efficient texture descriptor which allows the system to efficiently capture local structures. Every pixel in an image has a binary code produced corresponding to it by thresholding its value with that of the pixel. At a specific pixel position, the operator is thus defined as an proper set of binary comparisons of pixel intensities between the center pixel and its neighboring pixels. The LBP operator labels the pixels of the image by considering a neighborhood around each pixel and using the value of the center pixel to threshold the neighborhood.

A. 1D - Local Binary Pattern

1D-LBP method, which is obtained from the execution procedure of 2D-LBP was introduced by Chatlani et al. [22] in 1990 for the purpose of detecting speech signals that are non-stationary by nature. The fundamental task of a 1D-LBP is not so different from that of a texture operator [32]. A binary code is generated corresponding to every individual data sample in a signal by the thresholding of its value with that of the center sample. Through iteration, this method is realized over the whole signal. While applying LBP to EEG signal, m successive samples from the time series was considered to compute the LBP value for the $\frac{(m+1)}{2}th$ sample, which is acting as the center sample. The mathematical formulation of 1D LBP is akin to the 2D-LBP [39], although instead of the pixel intensities for the grid of pixels , amplitude value at every sample point is taken into consideration for the EEG time series. The difference of $j\ th$ neighbor sample with the amplitude value P_j and the center sample amplitude value P_c is known as decision variable s_j. m is an odd number denoting the consecutive sample numbers taken into account for coming up with the LBP codes. $f_j(s_j)$ is a value arrived by the application of the condition of threshold given in Equation (2).

$$s_j = P_j \text{-} P_c \tag{1}$$

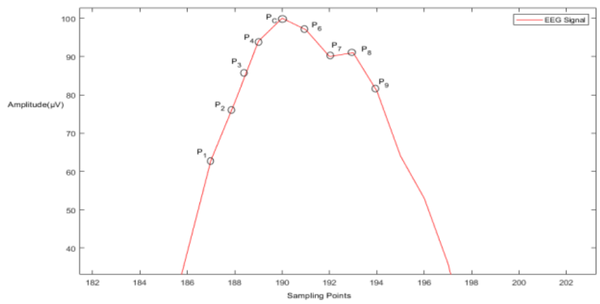
$$f_j(s_j) = \begin{cases} 1, & for,\ s_j \geq 0 \\ 0, & for\ ,\ s_j < 0 \end{cases} \tag{2}$$

LBP value concurring to P_c

$$LBP(k) = \sum_{j=1}^{[\frac{(m+1)}{2}]-1} f_j(s_j) * 2^j + \sum_{j=[\frac{(m+1)}{2}]+1}^{m} f_j(s_j) * 2^{j-1} \tag{3}$$

where k is the sample number that varies from 5 to (length of the signal – 4).

The procedure under taking in the calculation of 1D-LBP has been illustrated in Fig 2. These steps were repeated for all samples and over all the channels of EEG signals from the data considered. As this procedure was applied, an LBP signal was developed, which has values ranging from 0 to 255. Each LBP code represents unique wave shape and this wave shape is independent of magnitude [32].



(a)

P_1	P_2	P_3	P_4	P_c	P_6	P_7	P_8	P_9
38	62	78	94	100	97	90	91	81

(b)

P_1	P_2	P_3	P_4	P_c	P_6	P_7	P_8	P_9
0	0	0	0		0	0	0	0

(c)

P_1	P_2	P_3	P_4	P_c	P_6	P_7	P_8	P_9
				0				

(d)

Fig.2. (a) randomly selected section of EEG signal, (b) EEG amplitude of the signal shown in fig.2 (a), (c) Binary value of LBP corresponding to signal shown in fig.2 (a), and (d) LBP code equivalent to signal shown in fig.2 (a).

III. METHODOLOGY

The schematic representation of automatic recognition of abnormalities in EEG signals based on LBP codes is depicted in Fig. 3.

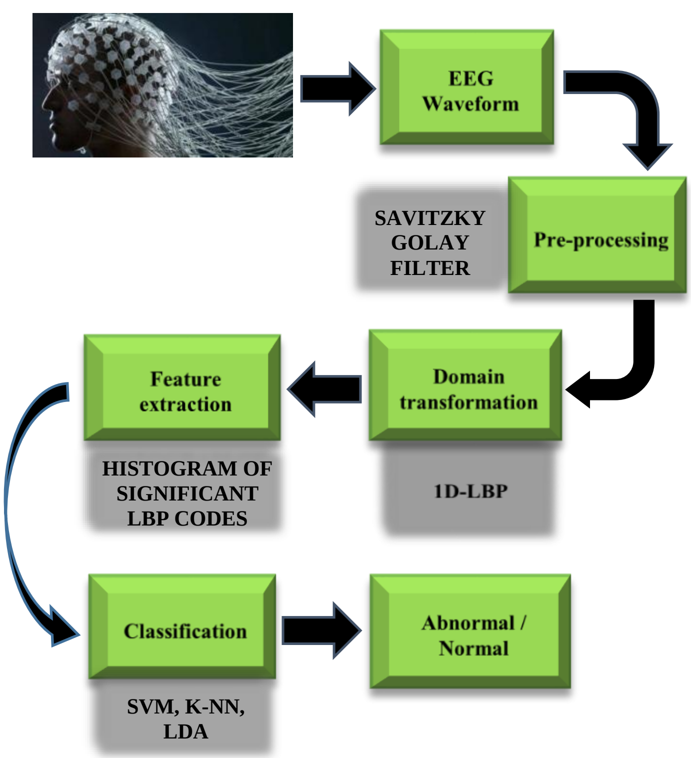


Fig.3. Proposed model: Block diagram.

The raw EEG signals are preprocessed by making use of Savitzky-Golay (SG) technique of filtration. The LBP of these pre-processed signals are calculated by considering consecutive samples. The LBP codes are analyzed to select the best codes by considering wave shape. The histogram of these selected LBP codes are calculated as features. The performance of these features are evaluated using three different classifiers namely SVM, KNN and LDA. A post-processing technique is employed to reduce FDR due to artifacts.

A. Preprocessing

EEG signals in the range of microvolts are observed on the scalp. External signals resulting from blinking of eyes, activities of facial muscles, etc. are added to the original signal. The presence of the above mentioned external artefacts and other noisy signals causes a significant complication in the analysis of EEGs. The EEG pre-processing is done to remove all the artefacts and external noise signals without any loss or damage to the crucial EEG components.

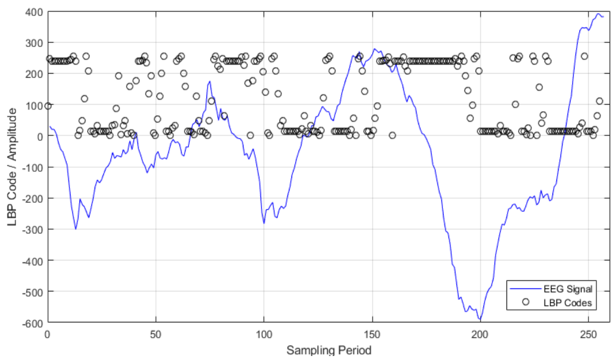
A commonly used low-pass filter, and well-adapted for smoothing the data, is Savitzky-Golay (SG) Filters [40]–[42]. SG filters are developed directly from a certain formulation of the smoothing problem contained in the time domain and filtering out a significant portion of the signals' high frequency content along with the noise. SG filters also minimize the errors caused by least-squares in placing a polynomial to the frames of noisy data. Typically, SG filter is applied to a sequence of digital data points that increase the signal-to-noise ratio (SNR) without distorting the signal. The subsets of consecutive data points are built-in using a low order polynomial with linear least square method, and convolution of all the polynomials is then obtained. The x is an independent variable whereas y is an observed value, data having a set of $n\,\{xj, yj\}$ points, where $j = 1, 2 \ldots n$, and can be represented with a set of m convolution coefficients, Ci, and given as,

$$Y_j = \sum_{i=\frac{-(m-1)}{2}}^{\frac{(m-1)}{2}} C_i Y_{j+i}\,, \left(\frac{m+1}{2}\right) \le j \le n - \left(\frac{m-1}{2}\right) \qquad (4)$$

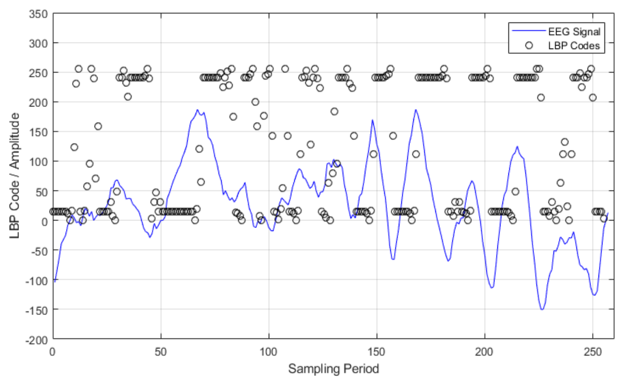
Execution of SG filter usually requires three inputs: the noisy signal (x), the order of the polynomial (k) and its frame size(f). The best proper values of k and f for a signal are generally assessed using trial and error method. Alternatively, the values can also be obtained using previously predicted values for a particular level of SNR for the given signal.

B. Feature Extraction

The normal and seizure signal can be distinguished by determining best attributes termed as features [43]. After preprocessing, feature extraction is the most key part before performing classification. LBP of the preprocessed EEG was calculated. Analysis of wave shape of each LBP code was done to find the best performing LBP codes. The LBP codes ranges from 0 to 255, and each code has unique wave shape independent of EEG signal amplitude. Fig. 4 shows casually selected fragment of EEG signal from patient 1 during seizure and normal, and the corresponding LBP values. From this figure, the frequency variations, phase change and smoothness characteristics (which are characteristics of seizure) can be identified by finding number of occurrences of LBP codes '0', '255', '15', '240','8','48', '112', and '143'. So, the histogram of these signals can be used as feature. This reduces feature vector dimension from 256 to 8. The uniqueness in wave shape of these mentioned codes are shown in Fig. 5. This selection is validated from Fig. 6 which shows box plot of selected LBP codes during seizure and normal period.

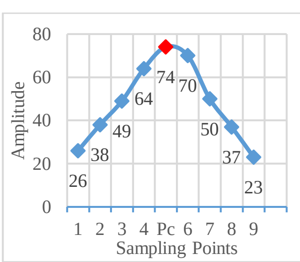


(a)

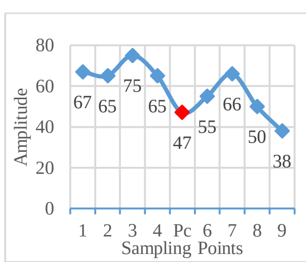


(b)

Fig.4. Random section of EEG signal and corresponding LBP codes during (a) seizure (b) normal periods.



(a)



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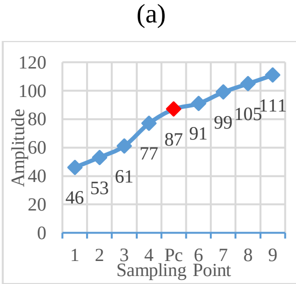
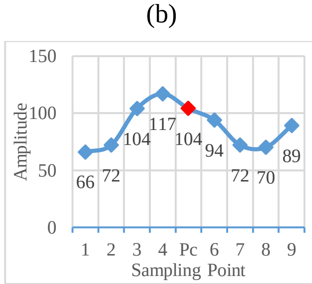


(c)



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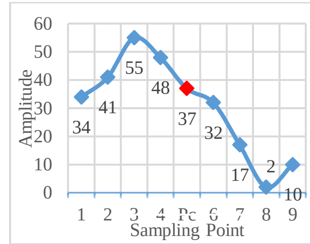
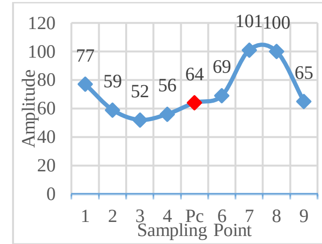
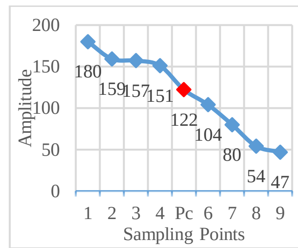


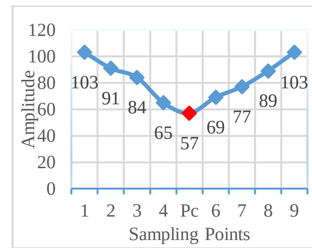
(e)



(f)



(g)



(h)

Fig.5. Wave shape corresponding to LBP codes (a) ‘0’, (b) ‘8’, (c) ‘15’, (d) ‘48’, (e) ‘112’, (f) ‘143’, (g) ‘240’, (h) ‘255’.

C. *Classification*

Automatic recognition of seizure can be viewed as a two class classification problem. So, performance of the selected feature was to be tested using different classifiers. Different methods have already been developed for the clustering and classification of EEG have already been developed [44]–[47]. Among these techniques, association rules, ANN [48], LDA [49], Gaussian mixture model (GMM) [48], *k*-means clustering [50], fuzzy logic [19], CNN [35], LSTM [37] and SVM [51] are used for epileptic seizure detection. When the relationships get complicated, automated techniques are applied to find them. It is clear from Fig. 6 that the histogram of selected LBP codes are good features for classification. The performance of present work has been tested on SVM, KNN and LDA classifiers.

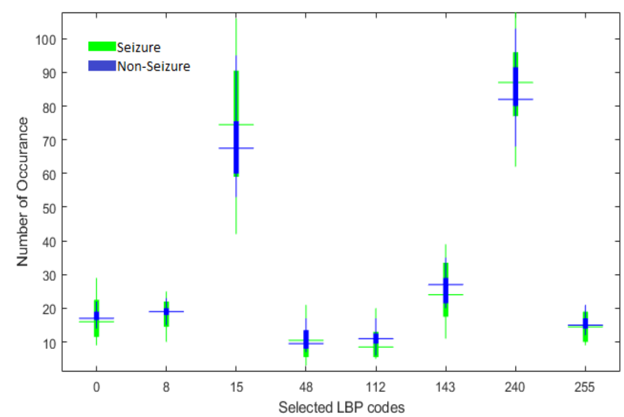


Fig.6. Boxplot of selected 8 LBP codes during seizure and normal period.

D. *Database Used*

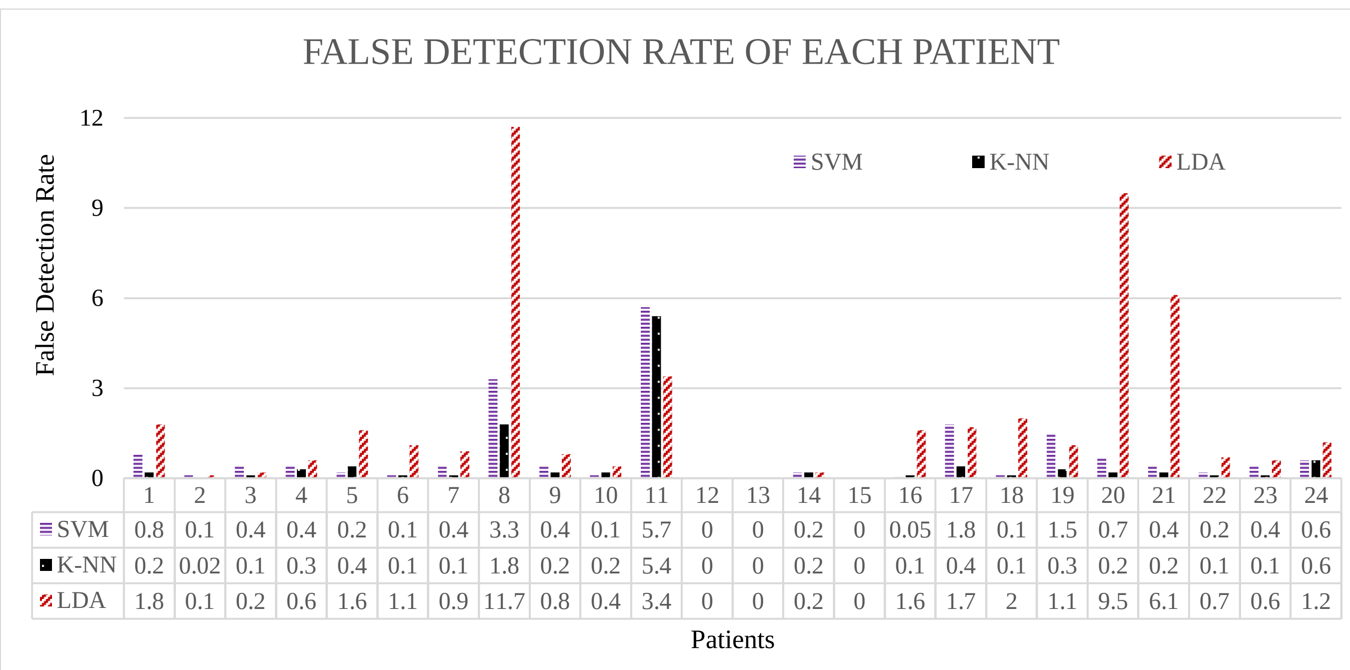
Publicly available CHB-MIT scalp EEG data from Children’s Hospital, Boston [29] was used in the present work, to compare the performance of this work with recent works. The database contained 916 hours of scalp EEG recording with intractable seizure recorded from 24 (23 pediatrics) patients. There were 664 EEG recording file from 5 males and 18 females, out of which 119 files consisted of 198 seizures. EEG signals were recorded at 256 samples per second with a resolution of 16 bits using 23 channels in most cases. The standard international 10-20 electrode placement system was used to record the EEG signals. The 15th and 23rd channels of the database shared the same configuration; the 23rd channel was left aside in the work, as an attempt to reduce redundancy. The patients with identical electrode montage were used for the performance evaluation. The patient details of CHB-MIT database are summarized in Table.1.

Table 1. Database used in the present study: Patient details

Patient	Gender	Age (years)	Duration (hours)	Number of seizures
P1	Female	11	40.5	7
P2	Male	11	35.5	3
P3	Female	14	37	7
P4	Male	22	155	4
P5	Female	7	39	5
P6	Female	1.5	66.7	10
P7	Female	14.5	67	3
P8	Male	3.5	20	5
P9	Female	10	67.9	4
P10	Male	3	50	7
P11	Female	12	33.8	3
P14	Female	9	25	8
P16	Female	7	17	8
P17	Female	12	21	3
P18	Female	19	35.6	6
P19	Female	6	29.9	3
P20	Female	13	27.6	8
P21	Female	9	32.8	4
P22	Female	6	31	3
P23	Female	-	26.5	7
P24	-	-	21.3	16
Total	-	-	879.9	124

IV. RESULTS

The raw EEG database from CHB-MIT EEG database was filtered using SG filter. LBP code for this preprocessed EEG signal were calculated by considering 8 neighboring points. Analysis of LBP codes was done, and the better-performing codes were selected by considering the wave shape. Histograms of the selected LBP codes were calculated as features that were fed to the classifiers. The classifier output was tested using three-fold cross validation wherein all seizures were tested by 30% hold out method. The classifier generates labels 1 and 0 for seizure and normal respectively. A post-processing technique was also included in order to cut false detection due to artifacts.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
SVM	0.8	0.1	0.4	0.4	0.2	0.1	0.4	3.3	0.4	0.1	5.7	0	0	0.2	0	0.05	1.8	0.1	1.5	0.7	0.4	0.2	0.4	0.6
K-NN	0.2	0.02	0.1	0.3	0.4	0.1	0.1	1.8	0.2	0.2	5.4	0	0	0.2	0	0.1	0.4	0.1	0.3	0.2	0.2	0.1	0.1	0.6
LDA	1.8	0.1	0.2	0.6	1.6	1.1	0.9	11.7	0.8	0.4	3.4	0	0	0.2	0	1.6	1.7	2	1.1	9.5	6.1	0.7	0.6	1.2

Fig.7. Patient-wise FDR of proposed seizure detection

A sensitivity of 100% for all subjects were achieved when tested on 124 seizures from 21 patients of CHBMIT EEG database for all classifiers considered. The patient-wise FDR is shown in Fig. 7 for three different classifiers. The least average FDR obtained for KNN is 0.52 when tested on 879.9 hours of data from 21 patients. The average sensitivity and FDR for the present algorithm is shown in Fig. 8.

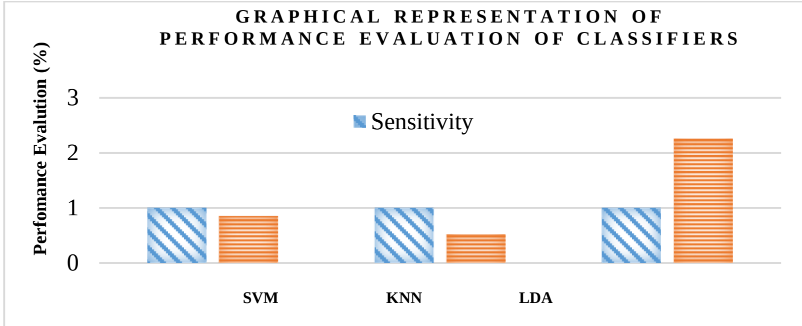


Fig.8. Average performance of the proposed seizure detection algorithm.

V. DISCUSSION

An algorithm for automatic recognition of epileptic seizure from EEG signals has been proposed. Table 2 represents performance comparison of present work with recent works. Though the present algorithm is simpler than others, highest sensitivity achieved is 100% when tested with 124 seizures from 21 patients. FDR values of 0.85, 0.52 and 2.26 are achieved for SVM, KNN and LDA classifiers respectively. All these results are comparable with other works as there was no seizure missed out of 124 seizures. Shanir et al [32] achieved a better FDR, but that work missed 4 seizures.

Table.2. Performance comparison of proposed seizure detection algorithm with recent works

Author	Database Used	Number of Patients	Number of Seizures	Feature Extraction	Classifier	Sensitivity (%)	False Detection Rate
Shoeb et al. [29] (2009)	CHB-MIT	23	163	Wavelet Transform	SVM	96	0.8
Nasehi et al. [52] (2013)	CHB-MIT	23	-	DWT	IPSONN	98	3
Viswanadhan et al. [53] (2014)	CHB-MIT	-	-	DWT	SVM	88.66	-
	Bonn University					95.67	
	Bern Barcelona					96	
Ahammad et al. [20] (2014)	CHB-MIT	23	41	Wavelet	LDA	98.6	-
P K Saleema et al. [28] (2015)	CHB-MIT	-	-	Wavelet Domain	LDA	96.06	-
Fergus et al. [54] (2016)	CHB-MIT	-	171	Frequency Parameters	KNN	88	-
Thodorof et al. [55] (2016)	CHB-MIT	23			RNN	95	1.7 – 0.8
Alickovic et al. [56] (2018)	CHB-MIT	-	-	DWT, EMD, WPD	SVM, KNN, RF, ANN	99.6	-
Tsiouris et al. [57] (2018)	CHB-MIT	23	185	STFT	-	88	8.1

Fan et al. [58] (2018)	CHB-MIT	23	182	Spectral Graph Theatric	Control Chart	98.48	-
Sopic et al. [59] (2018)	CHB-MIT	-	-	DWT	Decision Trees	93.80	-
Muhammad et al. [60] (2018)	CHB-MIT	23	173	1D &2D CNN features	SVM	92.35	-
Lu et al. [61] (2018)	CHB-MIT	23	-	Kraskov entropy based on the Hilbert Huang Transform (HHT), EMD, Kraskov entropy applied on tunable-Q wavelet transform	LS-SVM	74.93	-
Shanir et al. [32] (2018)	CHB-MIT	21	136	1D-LBP	K-NN	99.2	0.47
Present work	CHB-MIT	21	124	1D-LBP	SVM	100	0.85
					LDA	100	2.26
					K-NN	**100**	**0.52**

VI. CONCLUSIONS

EEG is a monitoring method to record electrical activity of the brain. The epileptic seizure is random and requires continuous monitoring of EEG, which may last for days. An LBP-based, patient-specific, automatic seizure detection algorithm has been proposed in the present work to assist neurologist in diagnosis, thereby improving the life of epileptic patients. The proposed algorithm has identified 8 morphologically significant LBP codes ‘0’, ‘8’, ‘15’, ‘48’, ‘112’, ‘143’, ‘240’ and ‘255’. The performance was evaluated using three different classifiers- SVM, KNN and LDA, using CHB-MIT EEG database. When tested on the CHB-MIT database considering 879.9 hours of scalp EEG recording from 21 patients having 124 seizures, the sensitivity is found to be 100% for all the classifiers selected. The corresponding FDR for these classifiers are 0.85, 0.52 and 2.26 respectively. The KNN classifier has shown the best performance, owing to its better feature-classifier combination. The present algorithm was developed for patient-specific seizure detection, and was applied only on offline epileptic EEG. So, the future work may consider patient-nonspecific detection, and applying on online EEG.

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