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Local pattern transformation based feature extraction techniques for classification of epileptic EEG signals

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ABSTRACT

Background and objective: According to the World Health Organization (WHO) epilepsy affects approximately 45–50 million people. Electroencephalogram (EEG) records the neurological activity in the brain and it is used to identify epilepsy. Visual inspection of EEG signals is a time-consuming process and it may lead to human error. Feature extraction and classification are two main steps that are required to build an automated epilepsy detection framework. Feature extraction reduces the dimensions of the input signal by retaining informative features and the classifier assigns a proper class label to the extracted feature vector. Our aim is to present effective feature extraction techniques for automated epileptic EEG signal classification.
Methods: In this study, two effective feature extraction techniques (Local Neighbor Descriptive Pattern [LNDP] and One-dimensional Local Gradient Pattern [1D-LGP]) have been introduced to classify epileptic EEG signals. The classification between epileptic seizure and non-seizure signals is performed using different machine learning classifiers. The benchmark epilepsy EEG dataset provided by the University of Bonn is used in this research. The classification performance is evaluated using 10-fold cross validation. The classifiers used are the Nearest Neighbor (NN), Support Vector Machine (SVM), Decision Tree (DT) and Artificial Neural Network (ANN). The experiments have been repeated for 50 times.
Results: LNDP and 1D-LGP feature extraction techniques with ANN classifier achieved the average classification accuracy of 99.82% and 99.80%, respectively, for the classification between normal and epileptic EEG signals. Eight different experimental cases were tested. The classification results were better than those of some existing methods.
Conclusions: This study suggests that LNDP and 1D-LGP could be effective feature extraction techniques for the classification of epileptic EEG signals.

1. Introduction

Epilepsy is a central nervous system disorder and it has been reported that approximately 45–50 million people suffer from this disorder [1]. EEG captures the neurological activity inside the brain by placing electrodes on the scalp and helps in detection of epileptic seizure [2,3]. Epileptic seizure detection can be considered as a classification problem where the task is to classify an input signal either as an epileptic seizure signal or as a non-seizure signal. EEG signals are usually recorded for long durations to carry out an analysis. Detection of epileptic seizure in these long duration EEG signals requires expertise. In the absence of expert, particularly in emergencies, seizure detection becomes a challenging task. Therefore, providing a framework for automated epileptic seizure detection is of great significance. A number of methods have been proposed in literature for the classification of epileptic EEG signals. The methods can be categorized into following domains of signal analysis:

Time domain analysis: Some techniques in the field of epileptic EEG signal classification belong to this category. Techniques like linear prediction [4], Fractional linear prediction [5], Principal component analysis based radial basis function neural network [6], etc. have been proposed for epileptic seizure detection.

Frequency domain analysis: With the assumption that the EEG signals are stationary signals, Polat and Gunes [7] introduced a hybrid framework based on frequency domain analysis with Fourier transform and decision tree. In the hybrid model, Fourier transform was used for feature extraction and decision tree was used for the classification. Srinivasan et al. [8] used features extracted from time domain and frequency domain for seizure detection in EEG signals. The extracted features were fed to the Elman neural network to detect epileptic seizure.

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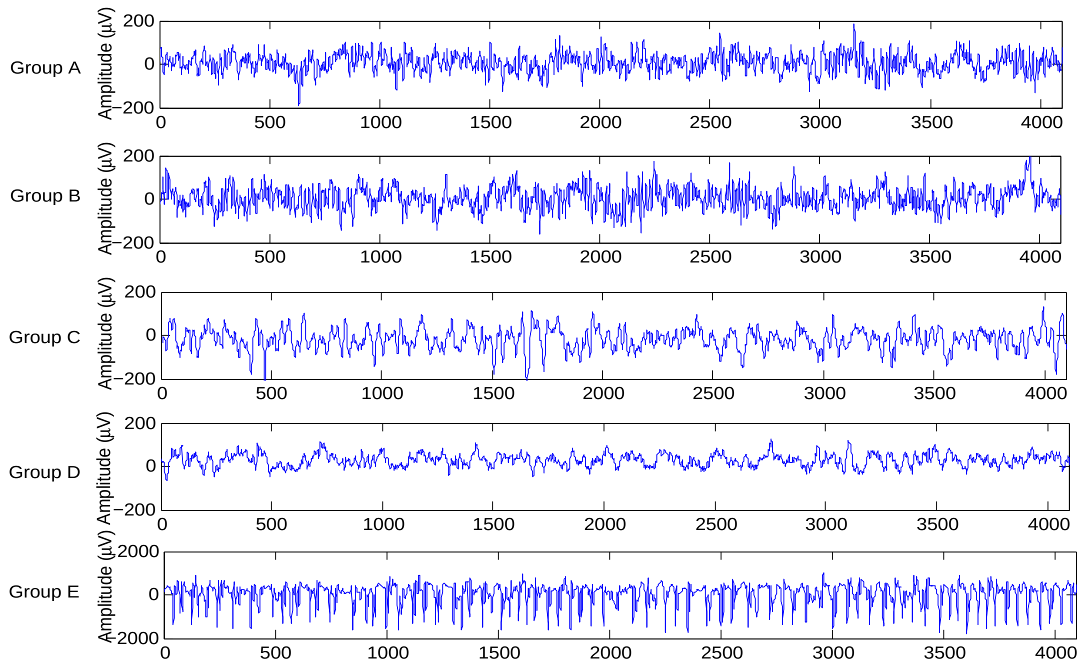

Fig. 1. Epilepsy Data Set.

Time–frequency domain analysis: It is well known that EEG signals are non-stationary signals. Considering the non-stationary property of EEG signals, feature extraction based on time–frequency image analysis with Hilbert-Huang transformation (HHT) was introduced for seizure classification [9]. Tzallas et al. [10] introduced a combined approach with time–frequency domain analysis for seizure detection. A number of methods have been proposed based on wavelet transform [11–15], multi-wavelet transform [16] for the detection of epileptic seizure. With the consideration of both the non-stationary and non-linearity properties of EEG signals, empirical mode decomposition (EMD) based method was introduced for the classification between normal and epileptic EEG signals [17].

Even though the above techniques have been used for epileptic EEG signal classification and other applications, one of the major issues associated with these techniques is the computational cost involved in the feature extraction step. Feature extraction techniques based on the local pattern transformation are computationally simple and widely used in different pattern recognition applications. One of such technique is the Local Binary Pattern (LBP). LBP has gained popularity in the field of face recognition [18], signal processing [19], speech processing [20], and epileptic EEG signal classification [21,22]. However, one limitation of LBP is its sensitiveness to local variation.

In this study, two effective feature extraction techniques called LNDP and 1D-LGP have been proposed for the classification of epileptic EEG signals. Both the techniques are computationally simple and insensitive to local and global variations. The insensitiveness of LNDP and 1D-LGP overcomes the limitation of 1D-LBP. These proposed techniques work in two phases. In the first phase, the local patterns are transformed and histogram formation is done. The histogram represents the feature vector of the corresponding EEG signal. Histogram classification is completed in the second phase. The histogram contains the structural information of the EEG signal. The classification has been carried out with four different machine learning classifiers. The classification performance is evaluated with 10-fold cross validation considering the sensitivity, specificity and accuracy.

The remaining content of this paper is organized as follows: methodology and materials used are discussed in Section 2. Experimental results are shown in Section 3. Finally, Section 4 concludes the article with future direction.

2. Methodology and materials

In this section, a brief discussion about the dataset, LNDP, 1D-LGP feature extraction techniques and the classifiers used has been done.

2.1. Dataset

In this study, the widely accepted publicly available benchmark data set provided by Department of Epileptology[1] at Bonn University, Germany has been used. The detailed description of the data set is provided in [23]. This benchmark data set consists of five groups (A, B, C, D, and E). There are 100 single-channel EEG signals in each group. Each EEG signal was recorded for 23.6 s containing 4097 sample points. These EEG signals were digitized through 12 bit A/D converter and the sampling frequency was set to 173.6 Hz. The groups A and B contains the EEG recording of five healthy volunteers while their eyes were opened and closed, respectively. The signals in groups C and D were recorded on patients before epileptic attack at hemisphere hippocampal formation and from the epileptogenic zone respectively. The EEG signals within group E were recorded from patients during the seizure activity. All the 5 groups have been used in this research. The EEG signal of each class is shown in Fig. 1.

2.2. Local transformation techniques

Recently, One-dimensional Local Binary Pattern (1D-LBP) has gained popularity in the field of EEG signal classification [21,22].

[1] EEG time series data sethttp://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3&changelang=3.

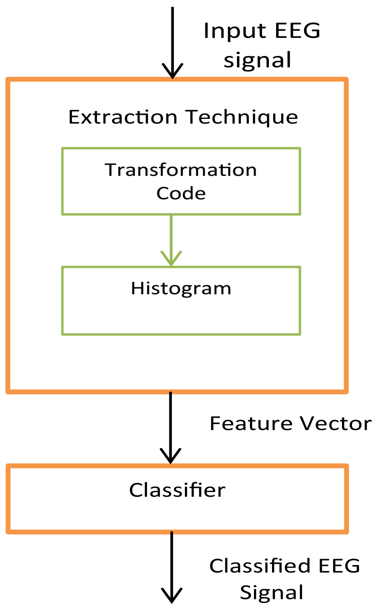

Fig. 2. Framework for epileptic EEG signal classification.

Each action or abnormality recorded in an EEG signal has some unique patterns. 1D-LBP focus on the local pattern structure of a signal during feature extraction and can detect these hidden patterns. However, a small change in the local pattern structure can affect the feature extraction process and hence the capability of 1D-LBP for detecting the hidden patterns is limited. Unlike 1D-LBP, the proposed LNDP and 1D-LGP techniques are insensitive to local variation. Both of these techniques are computationally simple like 1D-LBP. Moreover, both techniques are better than 1D-LBP for preserving the structural property of a pattern. In this section, LNDP and 1D-LGP feature extraction techniques are discussed one by one in details. Fig. 2 depicts the framework for the classification of EEG signals using these techniques.

2.3. Local Neighbor Descriptive Pattern (LNDP)

LNDP is a novel feature extraction technique based on local pattern transformation which captures the neighborhood relationship and preserves the structural property of the pattern. It is performed by comparing the value of the neighboring points in the pattern. The various steps of the LNDP feature extraction technique are as follows:

(1) Set the number of neighboring points m.
(2) For each signal point S_c, select $m/2$ number of neighbor points in forward and backward directions.
(3) Compute the difference of consecutive points.
The difference is computed as: $d_i = p_i - p_{i+1}$, for $i = 0, \ldots, m-1$.
(4) Compute the LNDP code.

$$S_c^{\mathrm{LNDP}} = \sum_{i=0}^{m-1} s(d_i)2^i \tag{1}$$

where

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{Otherwise} \end{cases}$$

The various steps involved in the LNDP are shown in Fig. 3.

2.4. One-dimensional Local Gradient Pattern (1D-LGP)

Like LBP, the LGP feature extraction technique was proposed for face recognition for two dimensional (2D) face images [18,24,25]. Even though the 1D-LBP feature extraction technique was proposed for signal processing [19] and successfully applied for epileptic EEG signal classification [21,22], the LGP based technique is yet to be proposed for the same. In this section, 1D-LGP based feature extraction technique has been introduced for epileptic EEG signal classification. 1D-LGP technique preserves the structural property of a pattern. The various steps of the proposed 1D-LGP feature extraction techniques are as follows:

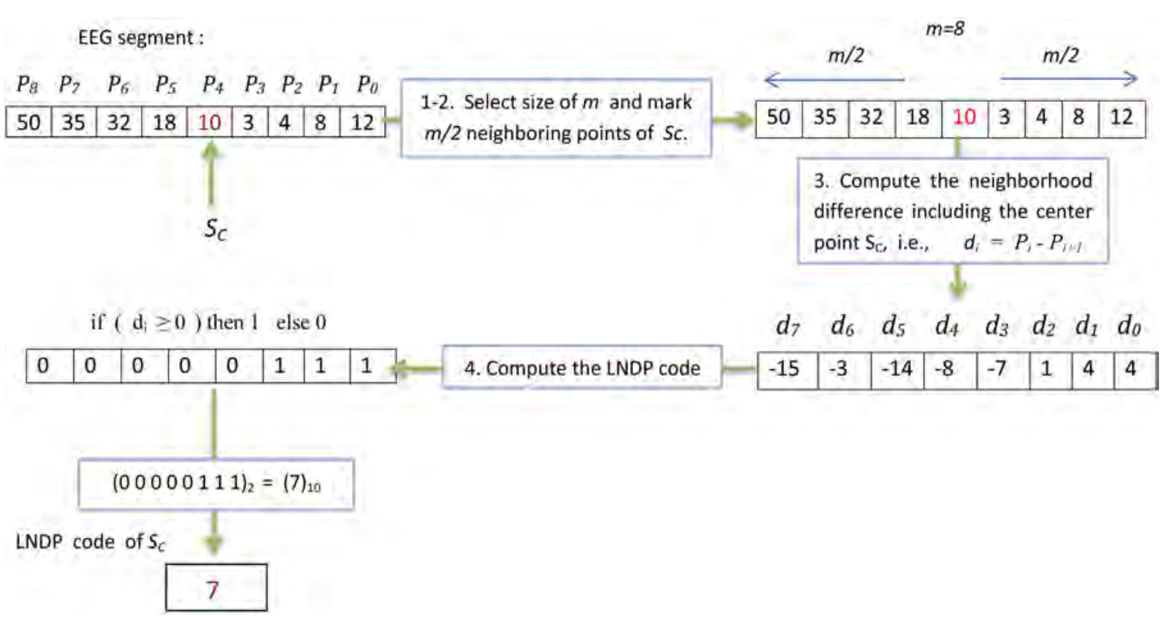

Fig. 3. LNDP code for the point S_c.

(1) Set the number of neighboring points m.
(2) For each signal point S_c, select $m/2$ number of neighbor points in forward and backward directions.
(3) Compute the gradient value of each neighboring point.
The gradient value is computed as: $g_i = |P_i - S_c|$, for $i = 0, \ldots, m-1$.
(4) Compute the mean gradient value.
The mean gradient value is computed as follows:

$$g_{avg} = \frac{1}{m}\sum_{i=0}^{m-1} g_i \tag{2}$$

(5) Compute the gradient code as: $gc_i = g_i - g_{avg}$, for $i = 0, \ldots, m-1$.
(6) Compute the 1D-LGP code.

$$S_c^{\text{1D-LGP}} = \sum_{i=0}^{m-1} s(gc_i)2^i \tag{3}$$

where

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{Otherwise} \end{cases}$$

A pictorial representation of various steps involved in the 1D-LGP technique is shown in Fig. 4.

2.5. 1D-LBP

In case of 1D-LBP [21], the transformation code for the signal point S_c is computed as follows:

$$S_c^{\text{1D-LBP}} = \sum_{i=0}^{m-1} s(P_i - S_c)2^i \tag{4}$$

where

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{Otherwise} \end{cases}$$

Once the transformation codes are obtained for all the signal points, the histogram of these codes formed the feature vector of the EEG signal and then fed to a classifier to perform the classification. The histogram contains the structural information of the local patterns.

2.6. 1D-LBP, LNDP, and 1D-LGP in case of similar patterns

One of the important properties of a local pattern transformation technique is to have the same transformation code for all the similar patterns. This issue is addressed in [25]. The behavior of 1D-LBP, 1D-LGP, and LNDP techniques in case of local and global variations for patterns with similar structures is shown in Fig. 5.

From the above figure it can be seen that even though all the three patterns have similar structures, the 1D-LBP code is different in case of local variation. On the other hand, both 1D-LGP and LNDP assigns the same transformation code to all the similar patterns.

2.7. 1D-LBP, LNDP, and 1D-LGP in case of dissimilar patterns

In the previous context, it has been shown how all these techniques work in case of similar patterns. Patterns with similar structural properties should be represented by the same transformation code. On the other hand, patterns with different structures should be represented by different transformation codes. The behavior of 1D-LBP, 1D-LGP, and LNDP techniques for patterns with different structures is shown in Fig. 6.

As shown in Fig. 6 all the three patterns have different structures. Even if the pattern structures are different, 1D-LBP assigns the same transformation code to the center point.

2.8. Histogram based feature vector

As described in previous sections, each transformation code represents the local pattern structure of a signal. The objective behind the histogram formation of these transformation codes is that signal structure can be represented by the distribution of these codes in a convenient form. The histogram graphically summarizes the structural distribution in two dimensional space, where the horizontal axis contains the range of transformation codes and the vertical axis contains the frequency (number of occurrences) of each code. Signals with similar structures will have similar graphical representations, whereas dissimilar signals will have different graphical representations. This graphical structure represents the feature vector and used for classification. A small segment of histogram features obtained with LNDP and 1D-LGP techniques for different groups under this study is shown in Fig. 7.

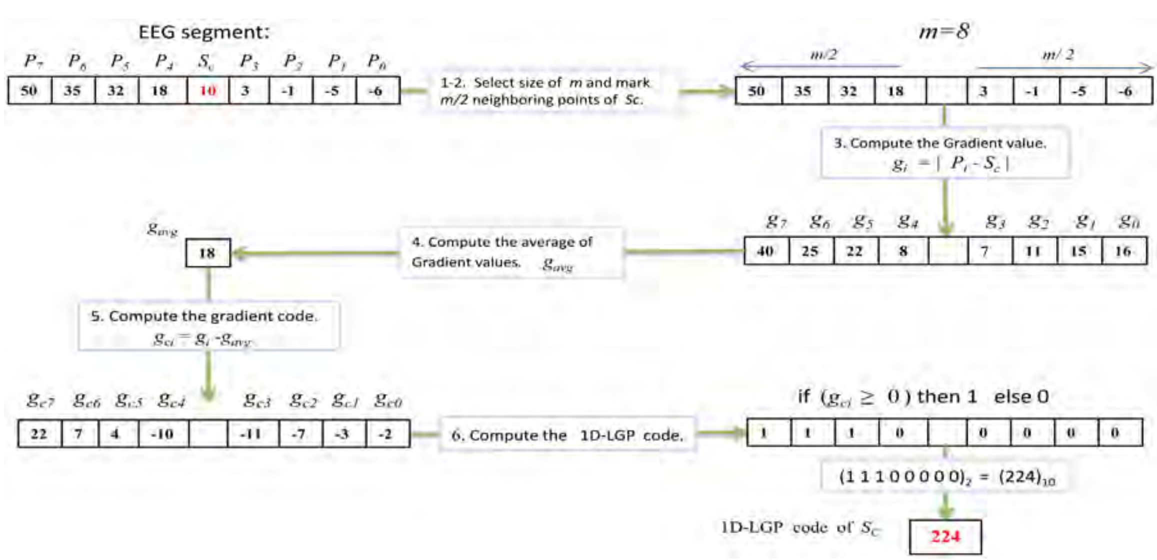

Fig. 4. 1D-LGP code for the point S_c.

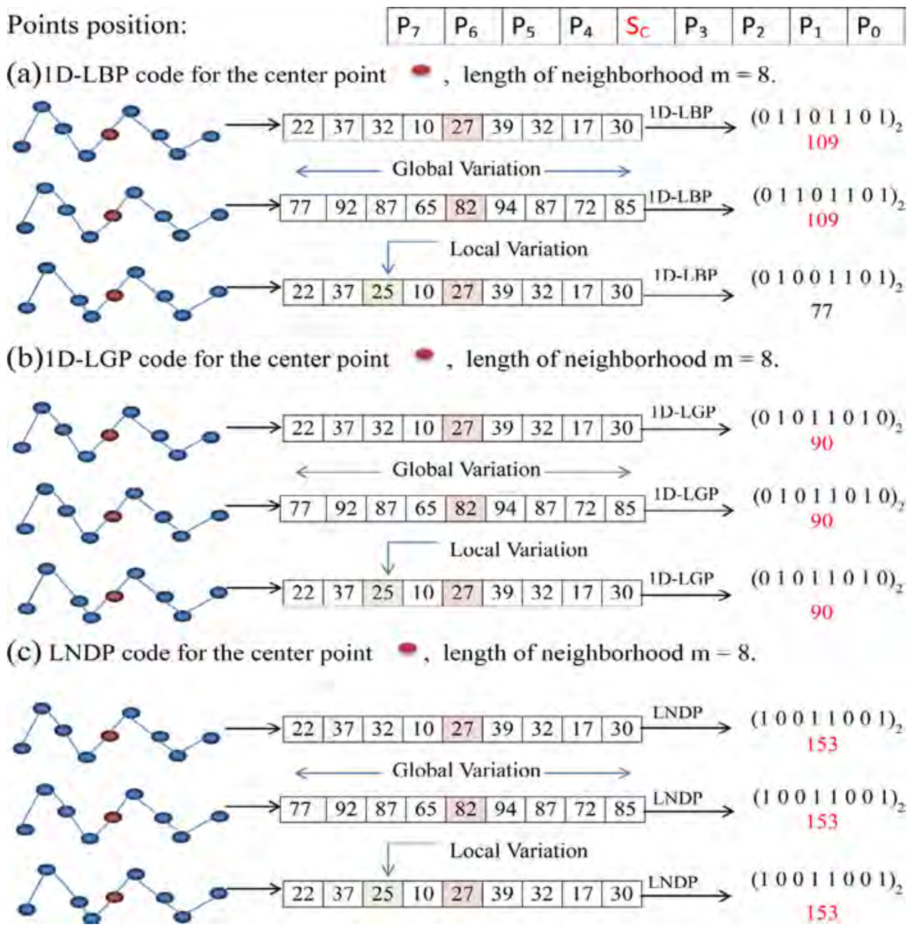

Fig. 5. (a) 1D-LBP, (b) 1D-LGP, and (c) LNDP for similar patterns. 1D-LGP and LNDP are insensitive to both local and global variations, whereas 1D-LBP is sensitive to local variation.

2.9. LNDP and 1D-LGP for one-dimensional (1D) signal processing

In this research, we have proposed LNDP and 1D-LGP for EEG signal processing. Like 1D-LBP [19], both the proposed techniques can also be considered for processing of other one-dimensional (1D) signals. For 1D signal processing, the transformation code for the signal point S_c considering m neighboring points ($P_0, P_1, \ldots, P_{m-1}$) could be computed from the following equations:

$$\mathrm{LNDP}_m(S_c) = \sum_{i=0}^{m-1} s(P_i - P_{i+1})2^i \tag{5}$$

$$1\mathrm{D}-\mathrm{LGP}_m(S_c) = \sum_{i=0}^{m-1} s(|P_i - S_c| - \frac{1}{m}\sum_{i=0}^{m-1}|P_i - S_c|)2^i \tag{6}$$

In both the equations the function $s(.)$ is given by:

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{Otherwise} \end{cases}$$

2.10. Time complexity of LNDP and 1D-LGP

Let S be a signal consisting of d points. Assume that m ($m < d$) neighboring points are considered for each signal point in order to compute the transformation code. In both the techniques (LNDP and 1D-LGP) m comparisons are required for generating the transformation code. Since there are d such points in the signal, the time complexity for processing the entire signal S is $O(d.\ m)$.

2.11. Classification

Once the transformation codes are obtained for all the signal points, the histogram is formed. The histogram represents the feature vector of the corresponding EEG signal and then fed to a classifier. Nearest Neighbor (NN), Decision Tree (DT), Support Vector Machine (SVM) and Artificial Neural Network (ANN) are some of the well known classifiers of machine learning and data mining [26]. In this study, all the above four classifiers have been used and the classification results have been shown.

2.12. Cross-validation

The experimental outcomes of the proposed technique are computed with 10-fold cross validation (10-fold CV). In 10-fold CV, the data set is divided into 10 parts. Out of these 10 parts, 9 parts are used as training set and the rest part is used as testing set. This process is repeated for 10 times with different training and testing sets. Usually, the mean accuracy of all the iterations represents the final accuracy [27].

2.13. Statistical parameters

The statistical parameters used for evaluating the performance of the proposed method are sensitivity (SEN), specificity (SPE), and accuracy (ACC). These are calculated as follows:

$$\mathrm{SEN}\,(\%) = \frac{TP}{TP + FN} \times 100 \tag{7}$$

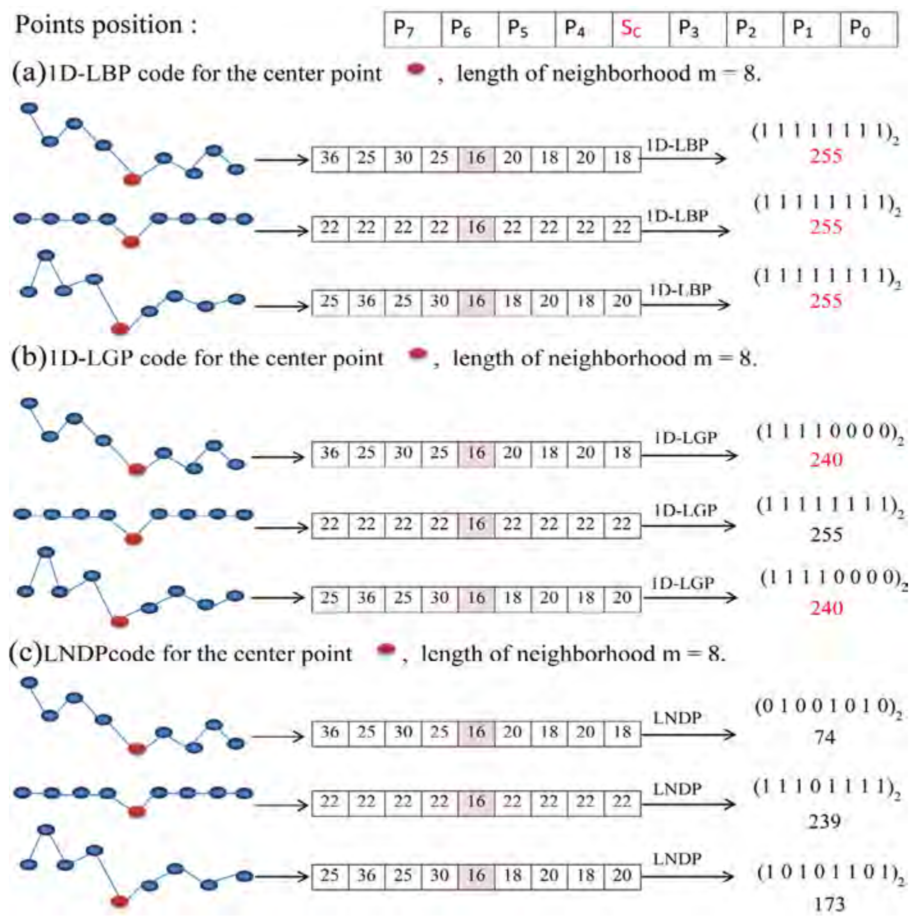

Fig. 6. (a) 1D-LBP, (b) 1D-LGP, and (c) LNDP for patterns with different structures. 1D-LBP assigned the same code for patterns with different structures.

$$\text{SPE}\,(\%) = \frac{TN}{TN + FP} \times 100 \tag{8}$$

$$\text{ACC}\,(\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{9}$$

where

TP (True Positive): correctly detected positive signals.
TN (True Negative): correctly detected negative signals.
FP (False Positive): erroneously detected positive signals.
FN (False Negative): erroneously detected negative signals.

3. Experimental results and discussion

In this section, the experimental results have been shown and the analysis of results has been carried out.

3.1. Results

All the five groups (A, B, C, D, and E) have been used in this study. In both techniques, the first step is the computation of transformation code for each signal point. Once the code computation for all the signal points of a signal is over, these codes are arranged in

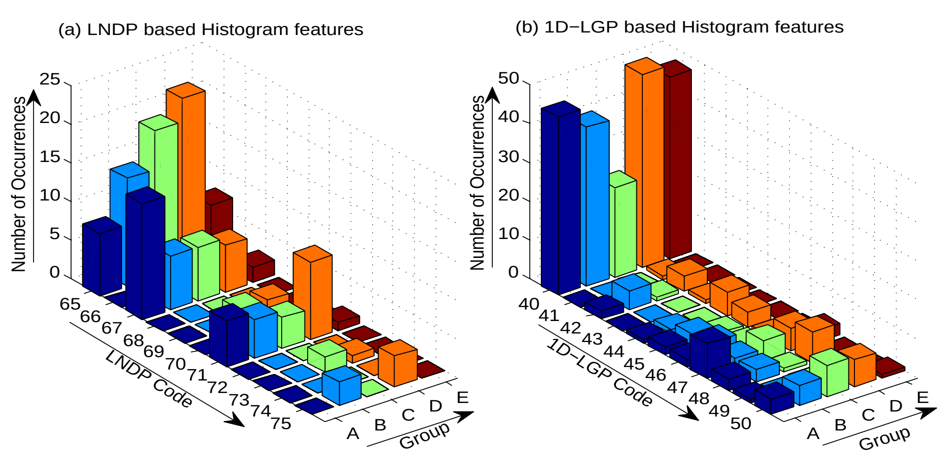

Fig. 7. Histogram features of different groups obtained with LNDP and 1D-LGP techniques.

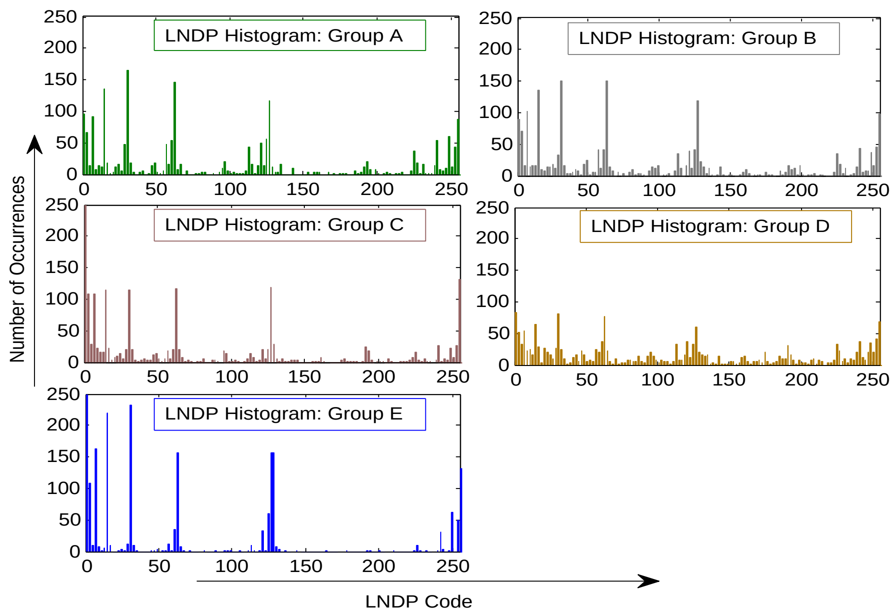

Fig. 8. LNDP histogram of EEG signals.

the form of a histogram. This process is repeated for all the signals. These histograms represent the feature vectors of the corresponding EEG signals and subsequently used for the classification using different machine learning classifiers. The LNDP and 1D-LGP based histograms of different groups are shown in Fig. 8 and Fig. 9 respectively.

The various experimental cases considered in this study have been shown in Table 1. Cases 1–7 deals with binary classification, whereas case 8 is a multi-class classification problem with three classes.

The length of the feature vector (l) depends on the number of neighboring points (m) considered in evaluating the transformation code and the relationship is given by the following equation:

$$l = 2^m \tag{10}$$

Table 1
Different experimental cases considered in this research.

Case	Groups	Description		
		Class 1	Class 2	Class 3
1	A–E	Healthy (eye open)	Ictal	–
2	B–E	Healthy (eye close)	Ictal	–
3	C–E	Inter-ictal	Ictal	–
4	D–E	Inter-ictal	Ictal	–
5	A–D	Healthy	Inter-ictal	–
6	CD–E	Inter-ictal	Ictal	–
7	ABCD–E	Non-seizure	Seizure	–
8	A–D–E	Healthy	Inter-ictal	Ictal

A number of experiments have been conducted and it is found that the best classification results are obtained when the number of neighboring points (m) is set to 8 and the length of the feature vector is 256. The performance of LNDP and 1D-LGP techniques

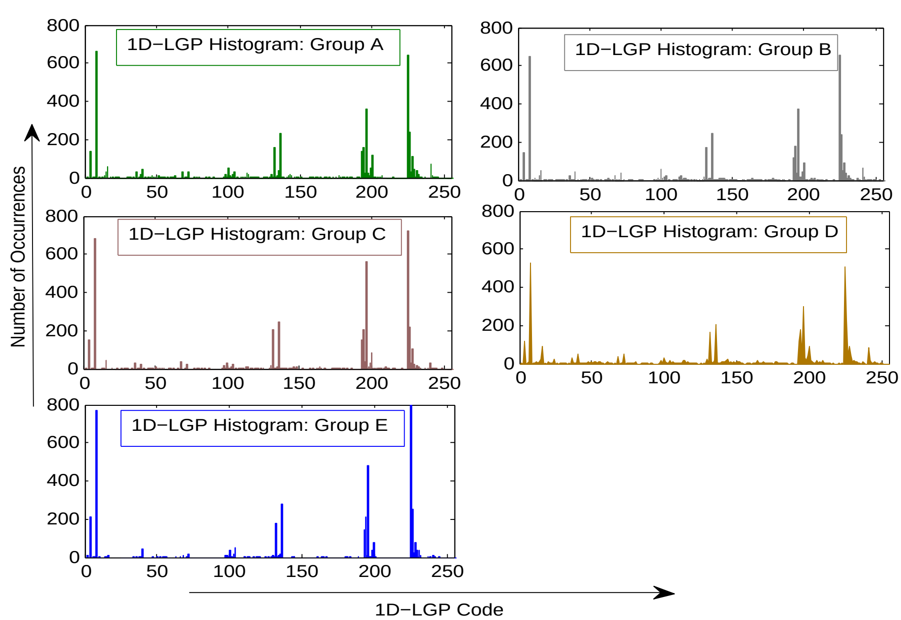

Fig. 9. 1D-LGP histogram of EEG signals.

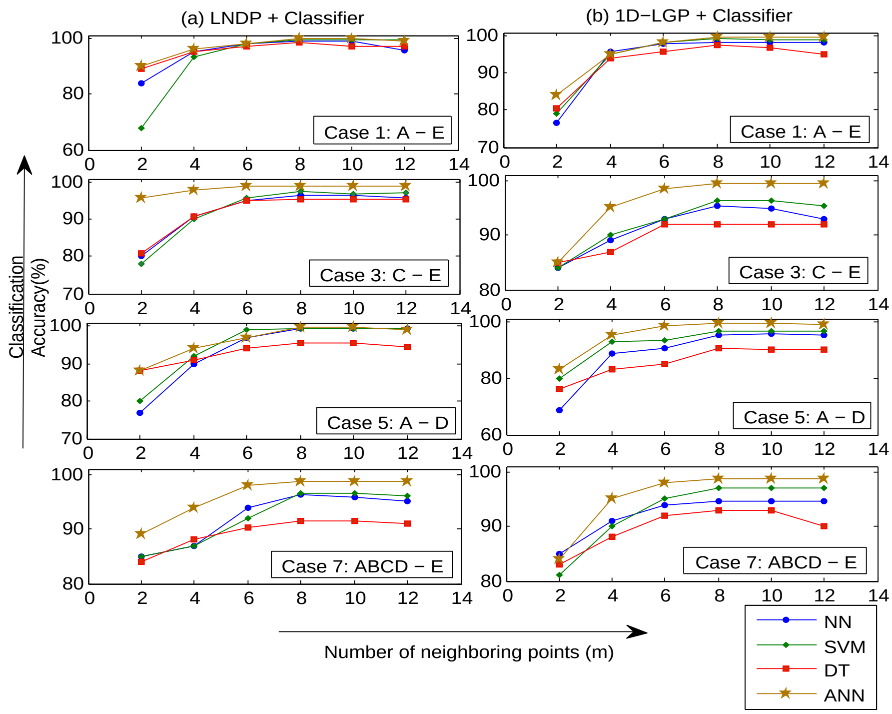

Fig. 10. Performance of LNDP and 1D-LGP with different number of neighboring points.

with different number of neighboring points for some experimental cases have been shown in Fig. 10.

For NN classifier with the Euclidean distance measure, the built-in MATLAB functions *ClassificationKNN.fit* and *predict* functions have been used for the training and testing the feature vector respectively. Similarly, for SVM, *svmtrain* and *svmclassify* functions have been used for training and testing the extracted feature vectors of EEG signals respectively. The SVM classifier has been trained with linear kernel function. Several experiments have been carried out to find the optimal values of the SVM kernel parameter using grid search. For the linear kernel, the value of the box constraint C is found to be 1. For decision tree, *fitctree* has been used to carry out the binary classification. The multilayer perceptron neural network consists of three layers. One input layer, one hidden layer, and the output layer. The *patternnet* function has been used to train the neural network. The number of nodes in the input layer represents the features of the input pattern. The error rate is set to 10^{-7} and the maximum number of iterations is set to 1000 for convergence. The scaled conjugate gradient method (*trainscg*) is used along with the hyperbolic tangent sigmoid (*tansig*) transfer function. The number of neurons in the hidden layer is set to 40. The experiments have been repeated for 50 times and the mean classification accuracy is computed. In all the experiments the *cvpartition* function has been used for the random selection of training and testing sets.

The mean classification accuracy (ACC) along with the standard deviation (SD) obtained for different experimental cases with LNDP and 1D-LGP along with the four machine learning classifiers has been shown in Table 2.

From the above table it can be seen that both LNDP and 1D-LGP techniques achieved the highest classification accuracy with ANN classifier. The sensitivity, specificity, and classification accuracy achieved along with the standard deviation for different experimental cases by LNDP and 1D-LGP techniques with ANN classifier have been shown in Table 3.

For real-life monitoring the feature extraction techniques should be computationally efficient. The entire dataset consist of 500 single channel EEG signals. The mean time required for feature extraction from a single channel EEG signal having 4097 points is computed with the proposed techniques and the results are shown in Table 4. The experiments have been performed on an Intel (R) core i7-4770 CPUs (3.40 GHz) with 4 GB of RAM.

It can be seen that the feature extraction techniques (LNDP, 1D-LBP, and 1D-LGP) are fast and required less than one millisecond for extracting features from the raw single channel EEG signal with 4097 points. As mentioned in the literature, discrete wavelet transform (DWT) is a well known technique in the field of epileptic seizure detection in EEG signal. Recently, it is reported thorough experimentation that the running time of 1D-LBP is less as compared to DWT [21]. In this research, it is found that the running time of the proposed LNDP technique is less than the running time of 1D-LBP for feature extraction.

In addition to 10-fold CV, another experiment has been conducted by randomly splitting the data into three distinct parts: train set (60%), test set (20%), and evaluation set (20%). Initially, for each experimental case, a model is built with the train set and test set such that the accuracy achieved by the classifier is maximized on the test set. Once the model is built, the performance of the classifier is evaluated using the same model and the evaluation set. The classification accuracy achieved on the test set, evaluation set and the total computational time (in second) required, including training and testing for different experimental cases with different classifiers have been shown in Tables 5 and 6.

As can be seen in Tables 5 and 6, LNDP and 1D-LGP achieved high classification accuracy for different experimental cases considered in this study. For most of the experimental cases, the ANN classifier achieved better classification accuracy. For case 1 (A–E), case 5 (A–D), and case 8 (A–D–E) LNDP achieved 100% accuracy on both the test set and evaluation set. For cases 2–4, the classification accuracy achieved on the evaluation set by LNDP technique is 97.50%, 100%, and 100% respectively. Similarly, the 1D-LGP techniques also achieved high classification accuracy for different experimental cases. For case 1, 1D-LGP achieved 100% classification accuracy on the evaluation set and 97.50% on the test set. For cases 2–5, 1D-LGP achieved the classification accuracy of 97.50%

Table 2
Mean classification accuracy (%) ± SD (%) of LNDP and 1D-LGP with different classifiers obtained with 50 runs of 10-fold cross validation.

Case number	Case name	LNDP + classifier				1D-LGP + classifier			
		NN	SVM	DT	ANN	NN	SVM	DT	ANN
1	A–E	99.00 ± 0.00	99.30 ± 0.25	96.12 ± 1.10	99.82 ± 0.24	98.47 ± 0.15	99.30 ± 0.29	97.55 ± 0.67	99.80 ± 0.25
2	B–E	95.92 ± 0.36	95.65 ± 0.96	93.05 ± 1.46	99.25 ± 0.52	95.27 ± 0.53	96.70 ± 0.92	92.55 ± 1.84	98.92 ± 1.45
3	C–E	96.65 ± 0.39	97.79 ± 0.44	95.60 ± 0.79	99.02 ± 0.60	95.40 ± 0.37	96.25 ± 0.53	91.97 ± 1.42	99.10 ± 0.83
4	D–E	93.97 ± 0.50	94.77 ± 1.14	92.82 ± 1.57	98.18 ± 0.92	91.17 ± 0.71	92.62 ± 0.81	88.69 ± 1.59	99.07 ± 0.44
5	A–D	99.50 ± 0.18	99.52 ± 0.37	95.60 ± 0.83	99.90 ± 0.20	95.17 ± 0.69	96.75 ± 0.60	90.47 ± 1.11	99.37 ± 0.39
6	CD–E	95.88 ± 0.44	96.26 ± 0.67	95.13 ± 0.80	98.88 ± 0.40	93.76 ± 0.32	95.26 ± 0.48	92.90 ± 0.91	98.78 ± 0.71
7	ABCD–E	96.35 ± 0.22	96.57 ± 0.46	91.52 ± 0.85	98.72 ± 0.42	94.71 ± 0.27	96.82 ± 0.26	92.88 ± 0.68	98.65 ± 0.36
8	A–D–E	90.93 ± 1.19	94.67 ± 1.12	89.00 ± 0.48	98.22 ± 0.45	90.28 ± 0.57	94.33 ± 0.88	88.00 ± 0.82	97.06 ± 0.62

Table 3
Sensitivity ± SD, specificity ± SD, and accuracy ± SD of LNDP and 1D-LGP techniques with ANN.

Case number	Case name	LNDP + ANN			1D-LGP + ANN		
		SEN ± SD (%)	SPE ± SD (%)	ACC ± SD (%)	SEN ± SD (%)	SPE ± SD (%)	ACC ± SD (%)
1	A–E	99.90 ± 0.307	99.75 ± 0.444	99.82 ± 0.247	99.60 ± 0.526	100.0 ± 00.00	99.80 ± 0.251
2	B–E	99.10 ± 0.743	99.40 ± 0.620	99.25 ± 0.521	98.60 ± 2.6636	99.25 ± 1.069	98.92 ± 1.453
3	C–E	98.55 ± 1.091	99.50 ± 0.607	99.02 ± 0.607	98.75 ± 1.292	99.45± 0.759	99.10 ± 0.836
4	D–E	97.20 ± 1.151	99.15± 1.089	98.18 ± 0.921	98.82 ± 0.632	99.32± 0.703	99.07 ± 0.449
5	A–D	99.85 ± 0.366	99.95± 0.223	99.90 ± 0.205	99.35 ± 0.587	99.40 ± 0.680	99.37 ± 0.393
6	CD–E	97.05 ± 0.686	99.80 ± 0.377	98.88 ± 0.408	97.20 ± 1.704	99.57 ± 0.466	98.78 ± 0.714
7	ABCD–E	98.30 ± 1.101	98.82 ± 0.333	98.72 ± 0.428	98.44 ± 0.822	98.70 ± 0.789	98.65 ± 0.362
8	A–D–E	–	–	98.22 ± 0.455	–	–	97.06 ± 0.623

Table 4
Computational time (in seconds) required for feature extraction from a single-channel EEG signal.

Feature extraction technique	Number of signals	Total time (in s)	Mean time (in s) ± SD (%)
LNDP	500	24.46	0.048 ± 0.19
1D-LBP	500	35.56	0.071 ± 0.44
1D-LGP	500	41.34	0.082 ± 0.37

Table 5
Classification accuracy (%) on the test set, evaluation set [total computational time (in second) for training and classification with the training set, evaluation set and test set after feature extraction] with LNDP and different classifiers.

Case	Classification accuracy (%) on test set, evaluation set [total time] with LNDP			
	NN	SVM	DT	ANN
A–E	97.50, 100.0 [0.122]	100.0, 100.0 [0.162]	95.00, 100.0 [0.203]	100.0, 100.0 [0.896]
B–E	90.00, 97.50 [0.128]	95.00, 97.50 [0.161]	90.00, 95.00 [0.197]	97.50, 97.50 [0.888]
C–E	95.00, 100.0 [0.121]	92.50, 100.0 [0.156]	92.50, 95.00 [0.209]	97.50, 100.0 [0.912]
D–E	92.50, 100.0 [0.124]	95.00, 95.00 [0.161]	97.50, 97.50 [0.201]	97.50, 100.0 [0.812]
A–D	100.0, 100.0 [0.121]	100.0, 100.0 [0.162]	95.50, 97.50 [0.199]	100.0, 100.0 [0.914]
CD–E	95.00, 99.33 [0.128]	95.00, 95.00 [0.167]	98.33, 98.33 [0.223]	98.33, 100.0 [1.211]
ABCD–E	93.00, 99.00 [0.137]	95.00, 95.00 [0.196]	90.00, 90.00 [0.322]	98.33, 100.0 [1.432]
A–D–E	95.00, 93.33 [0.126]	94.44, 93.33 [0.182]	85.00, 96.67 [0.237]	100.0, 100.0 [0.985]

on the evaluation set. Both the techniques achieved high classification accuracy for other experimental cases as well. Because of the randomness, it is also found that for some experimental cases the accuracy achieved on the test set is better as compared to the evaluation set. The total computational time for the training and classification of EEG signals is found to be less for different classifiers. Nearest Neighbor classifier took least time for training and classification, whereas ANN classifier took highest time and also achieved better classification accuracy for different experimental cases.

Table 6
Classification accuracy (%) on the test set, evaluation set [total computational time for training and classification with the training set, evaluation set and test set after feature extraction] with 1D-LGP and different classifiers.

Case	Classification accuracy (%) on test set, evaluation set [total time] with LNDP			
	NN	SVM	DT	ANN
A–E	97.50, 100.0 [0.122]	100.0, 100.0 [0.162]	95.00, 100.0 [0.203]	100.0, 100.0 [0.896]
B–E	90.00, 97.50 [0.128]	95.00, 97.50 [0.161]	90.00, 95.00 [0.197]	97.50, 97.50 [0.888]
C–E	95.00, 100.0 [0.121]	92.50, 100.0 [0.156]	92.50, 95.00 [0.209]	97.50, 100.0 [0.912]
D–E	92.50, 100.0 [0.124]	95.00, 95.00 [0.161]	97.50, 97.50 [0.201]	97.50, 100.0 [0.812]
A–D	100.0, 100.0 [0.121]	100.0, 100.0 [0.162]	95.50, 97.50 [0.199]	100.0, 100.0 [0.914]
CD–E	95.00, 99.33 [0.128]	95.00, 95.00 [0.167]	98.33, 98.33 [0.223]	98.33, 100.0 [1.211]
ABCD–E	93.00, 99.00 [0.137]	95.00, 95.00 [0.196]	90.00, 90.00 [0.322]	98.33, 100.0 [1.432]
A–D–E	95.00, 93.33 [0.126]	94.44, 93.33 [0.182]	85.00, 96.67 [0.237]	100.0, 100.0 [0.985]

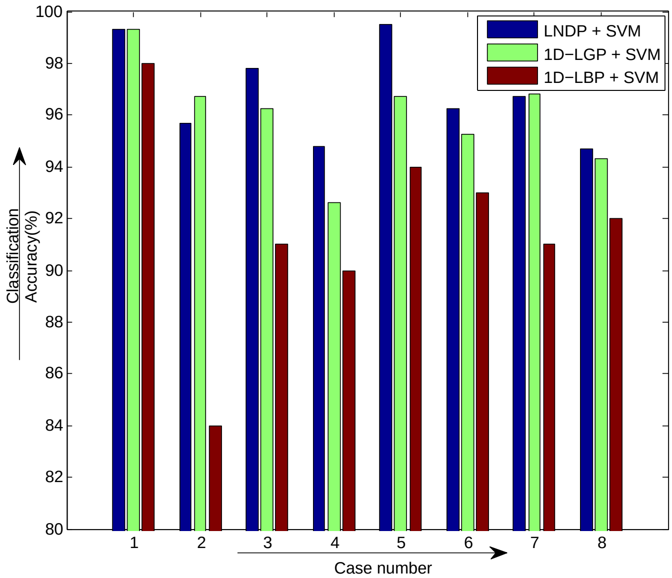

Fig. 11. Mean classification accuracy (%) of LNDP, 1D-LGP, and 1D-LBP techniques for different experimental cases achieved with 50 runs of 10-fold CV.

The classification accuracy achieved by SVM with 1D-LBP [21], LNDP and 1D-LGP feature extraction techniques (with the same number of features and same parameter setting) for different experimental cases have been shown in Fig. 11. It is found that for most of the experimental cases the proposed approaches achieved better classification accuracy as compared to 1D-LBP.

3.2. Discussion

First of all, in order to conduct a fair comparison of the proposed techniques with other methods proposed in the literature, the performance of the proposed techniques is evaluated with the benchmark EEG time series data set. The following observations are made from the experimental results. LNDP and 1D-LGP feature extraction techniques have been able to achieve an high classification accuracy with ANN classifier. In the literature, many of the researchers have focused on case 1 (A–E). In this study, eight different experimental cases have been considered as shown in Table 1. The classification accuracy of the proposed techniques (evaluated with 50 runs of 10-fold CV) and different methods reported in the literature have been shown in Table 7. It should be noted that most of the recent methods shown in Table 7 were evaluated using 10-fold CV.

For case 1 (A–E), the best classification accuracy reported in the literature is 100% which was achieved by Srinivasan et al. [33] with the application of entropy and neural network. Similarly, the classification accuracy of 100% was achieved by Iscan et al. [34] with the combination of time–frequency domain features. The highest classification accuracy of 100% has also been reported with genetic programming [31] and dual tree-complex wavelet transform (DTCWT) [28,29]. For this experimental case, LNDP and 1D-LGP achieved the average classification accuracy of 99.82% and 99.80% respectively. These classification accuracies are better than better than the classification accuracy of 98.17% reported by Lee et al. [39]. Recently, Fu et al. [38] reported 99.125% classification accuracy for the same case 1.

For cases 2–4, the classification accuracy (%) achieved by the LNDP is 99.25, 99.02, and 98.18 respectively. Similarly, with 1D-LGP the accuracy obtained is 98.92, 99.10 and 99.07 respectively. Nicolaou and Georgiou [45] reported the classification accuracy of 82.88, 88.00, and 78.98 for these experimental cases with the

Table 7
Authors, year, methods and classification accuracy obtained for some cases in the literature.

Authors	Year	Methods	Cases	Accuracy(%)
–	–	–	**Case 1**	–
[28]	2016	DTCWT + CVANN	A–E	100
[29]	2016	DTCWT + GRNN	A–E	100
[30]	2014	Fuzzy approximate entropy and SVM	A–E	100
[31]	2013	Genetic programming	A–E	100
[32]	2013	wavelet-based sparse function + NN	A–E	100
[33]	2007	Approximate entropy and ANN	A–E	100
[34]	2011	Time and Frequency features	A–E	100
[35]	2011	DWT + k-mean and ANN	A–E	100
[16]	2010	Approximate entropy and ANN	A–E	99.85
		LNDP + ANN **(Proposed work)**	A–E	99.82
		1D-LGP + ANN **(Proposed work)**	A–E	99.80
[8]	2005	Time–frequency domain features with neural network	A–E	99.60
[36]	2015	Weighted Permutation Entropy + SVM	A–E	99.50
[21]	2014	1D-LBP + Functional Tree	A–E	99.50
[37]	2011	Wavelet entropy	A–E	99-100
[38]	2014	Time–frequency image using HHT and SVM	A–E	99.125
[7]	2007	Fast Fourier transform and decision tree classifier	A–E	98.70
[39]	2014	Wavelet transform, phase–space reconstruction with Euclidean distance	A–E	98.17
[40]	2004	Neural network	A–E	97.50
[41]	2012	Wavelet transform and ANN	A–E	96.00
[12]	2009	Discrete wavelet transform and approximate entropy	A–E	96.00
[42]	2009	cross correlation and SVM	A–E	95.50
[43]	2009	wavelet energy and ANN	A–E	95.20
[44]	2012	HOS-PCA + LR	A–E	94.50
[13]	2007	Wavelet feature extraction and a mixture of expert model	A–E	94.50
[45]	2012	Permutation entropy and SVM	A–E	93.55
[46]	2005	Entropies	A–E	92.22
[47]	2007	Time–frequency analysis with Artificial Neural Networks(ANN)	A–E	85.90
–	–	–	**Case 2**	–
[29]	2016	DTCWT + GRNN	B–E	100
[30]	2014	Fuzzy approximate entropy and SVM	B–E	100
		LNDP + ANN **(Proposed work)**	B–E	99.25
		1D-LGP + ANN **(Proposed work)**	B–E	98.92
[36]	2015	Weighted Permutation Entropy + SVM	B–E	85.00
[45]	2012	Permutation entropy and SVM	B–E	82.88
–	–	–	**Case 3**	–
[29]	2016	DTCWT + GRNN	C–E	100

Table 7 (*Continued*)

Authors	Year	Methods	Cases	Accuracy(%)
[30]	2014	Fuzzy approximate entropy and SVM	C–E	99.60
		1D–LGP + ANN **(Proposed work)**	C–E	99.10
		LNDP + ANN **(Proposed work)**	C–E	99.02
[36]	2015	Weighted Permutation Entropy + SVM	C–E	93.50
[45]	2012	Permutation entropy and SVM	C–E	88.00
–	–	–	**Case 4**	–
		1D-LGP + ANN **(Proposed work)**	D–E	99.07
		LNDP + ANN **(Proposed work)**	D–E	98.18
[29]	2016	DTCWT + GRNN	D–E	98.00
[36]	2015	Weighted Permutation Entropy + SVM	D–E	96.50
[30]	2014	Fuzzy approximate entropy and SVM	D–E	95.85
[21]	2014	1D–LBP + BayesNet	D–E	95.50
[45]	2012	Permutation entropy and SVM	D–E	79.94
–	–	–	**Case 5**	–
		LNDP + ANN **(Proposed work)**	A–D	99.90
[21]	2014	1D–LBP + BayesNet	A–D	99.50
		1D-LGP + ANN **(Proposed work)**	A–D	99.37
–	–	–	**Case 6**	–
		LNDP + ANN **(Proposed work)**	CD–E	98.88
		1D-LGP + ANN **(Proposed work)**	CD–E	98.78
[29]	2016	DTCWT + GRNN	CD–E	98.67
[48]	2015	IMFs and LS-SVM classifier	CD–E	98.67
[22]	2015	Gabor filter + 1D-LBP + NN	CD–E	98.33
[21]	2014	1D-LBP + BayesNet	CD–E	97.00
[5]	2014	Fractional linear prediction	CD–E	95.33
–	–	–	**Case 7**	–
[32]	2013	wavelet-based sparse function + NN	ABCD–E	100
[31]	2013	Genetic programming	ABCD–E	100
[28]	2016	DTCWT + CVANN	ABCD–E	99.15
		LNDP + ANN **(Proposed work)**	ABCD–E	98.72
		1D-LGP + ANN **(Proposed work)**	ABCD–E	98.65
[16]	2010	Approximate entropy and ANN	ABCD–E	98.27
[30]	2014	Fuzzy approximate entropy and SVM	ABCD–E	97.38
–	–	–	**Case 8**	–
[28]	2016	DTCWT + CVANN	A–D–E	99.30
[31]	2013	Genetic programming	A–D–E	99.25
		LNDP + ANN **(Proposed work)**	A–D–E	98.22
		1D-LGP + ANN **(Proposed work)**	A–D–E	97.06
[35]	2011	DWT + k-mean and ANN	A–D–E	96.67
[30]	2014	Fuzzy approximate entropy and SVM	A–D–E	95.67
[21]	2014	1D-LBP + BayesNet	A–D–E	95.67

combination of permutation entropy and SVM. Recently, Kumar et al. [30] conducted several experiments and achieved a maximum classification accuracy (%) of 100, 99.60, and 95.85 for these experimental cases respectively.

For cases 5–7, LNDP and 1D-LGP achieved the classification accuracy (%) of 99.90, 98.88, 98.72 and 99.37, 98.78, 98.65 respectively. For case 6 (CD–E), Joshi et al. [5] reported the classification accuracy (%) of 95.33 with the application of fractional linear prediction technique. Sharma and pachori [48] reported the classification accuracy of 98.67% for the same case. For case 7 (ABCD–E), Kumar et al. [30] achieved the accuracy of 97.38% with the application of approximate entropy and SVM. For this case, the highest classification accuracy of 100% was reported with genetic programming [31].

Experimental case 8 (A–D–E) is a multi-class classification problem including three classes. The classification accuracy achieved by LNDP is 98.22% and by 1D-LGP is 97.06%. For this multi-class classification task, Orhan et al. [35] achieved the classification accuracy of 96.67% with the combination of wavelet transform, k-mean clustering, and ANN classifier. Recently, Kaya et al. [21] reported the classification accuracy of 95.67% with 1D-LBP. Peker et al. [28] achieved the highest accuracy of 99.30% by using DTCWT for this multi-class classification problem.

These experimental results show that both LNDP and 1D-LGP have been able to achieve high classification accuracy (Table 7).

4. Conclusions

In this study, two effective feature extraction techniques (LNDP and 1D-LGP) based on local pattern transformation have been introduced for epileptic EEG signal classification. Both the techniques focus on local patterns and extract informative features for classification. The proposed techniques are computationally simple and easy to implement. The effectiveness of these techniques has been evaluated with the benchmark EEG time series dataset. The machine learning classifiers used are NN, SVM, ANN, and DT. Both the feature extraction techniques achieved better classification accuracy with ANN classifier. For the classification between normal and epileptic EEG signals, LNDP and 1D-LGP achieved the average classification accuracy of 99.82% and 99.80% respectively. Along with this, eight different experimental cases have been conducted. The experimental results show that LNDP and 1D-LGP could be effective feature extraction techniques for EEG signal classification. In future, both techniques can also be considered for processing other 1D signals.

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