Seizure Detection with Local Binary Pattern and CNN Classifier

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Abstract. The present work proposes two novel approaches namely One Dimensional adaptive average Local Binary Pattern (1-D AaLBP) and One-Dimensional adaptive difference Local Binary Pattern (1-D AdLBP) for feature extraction from EEG signals and Convolutional Neural Network (CNN) for classification of EEG signals. Both the proposed feature extraction methods are computationally easy to implement. In the first step the histograms are formed from the extracted patterns, after that feature vectors of the histogram are given as input to the classifier. Two benchmark EEG datasets such as Bonn and CHB-MIT are employed for conducting experiments for comparing the performances of the proposed method with other existing research works. The performance measures such as sensitivity, specificity, classification accuracy and execution time are used for evaluating the proposed methods. It is learned from the experiments conducted that among various methods the proposed method provides improved performance in terms of sensitivity, specificity, classification accuracy and execution time.

1. Introduction
Epileptic seizure is the most common brain disorder by which approximately fifty million people are affected in all over the world and possibly it can be diagnosed by classifying Electroencephalogram (EEG) data [1]. Detection of epileptic-seizure is done through manual scanning of EEG records, which is a complex and time-consuming process. Over the last few eras, numbers of researches on various methods by classifying EEG data have been presented for epileptic seizure detection [2]. EEG is a signal which contains details of the electrical activity of the brain produced by the neurons. EEG signal is captured by using a surface and scalp electrodes with different size of channel systems [3]. Since EEG signals are time series data, feature are extracted in time domain and are used for analysing EEG pattern [4]. Min, Max, Average are the general statistical features applied for epileptic-seizure detection which requires less computation time and are easy to implement [5]. Frequency-domain feature like PSD and Entropy were also efficiently applied in detection of seizure [6]. Time-Frequency feature like wavelet based approximate entropy, Lyapunov exponent and correlation dimension as well used for epileptic-seizure detection and provides better performance [7]. The number of recent research works is carried out in the area of epileptic seizure detection using EEG signals. A parallel nonlinear transformation framework to transform the nonlinear wavelet-transform coefficients into a set of independent scalar coefficients was proposed. Based on these scalar coefficients, features election strategy was proposed on the transformed feature domain. A 1-D LBP system was proposed for signal processing [8]. Though time domain and frequency domain statistical features are easy to compute they provide lesser performance in seizure detection. Thus recently, the 1D-LBP technique has been used for epileptic-seizure detection by applying EEG signal classification [9, 10]. 1D-LBP focuses on the local pattern of
a signal to extract valued features for classification. However, 1D-LBP is sensitive to local variation. Local variation refers to any structural change in the local pattern of a signal.

Mostly picking the finest features for classification is crucial for classifier carrying into the action. Multiple feature may provide duplication of information which is complex in classification systems [11]. Hence selecting features is important in providing better results. Recently Fuzzy based feature selection approach has been used for epileptic-seizure detection [12]. There exists various traditional and advanced classifications techniques available for classification of EEG data, among the various classification techniques, Recently CNN has been applied as an efficient classifier in the domain of seizure detection and it provided superior performance over other existing classifiers [13]. Experimental results demonstrated that the proposed method provides better efficiency in detecting an epileptic seizure. The remaining content of the article is organized as follows: Methodology and materials, Experimental results and Conclusion & possible future work.

2. Methodology and Materials
2.1 Dataset Description

Bonn Dataset
Bonn is a benchmark Electroencephalogram database, which is popularly used by many researchers in detection of epileptic-seizure [14]. This data is publicly available in University of Bonn website, which is a five-class dataset. Each set has hundred signals recorded with 23.6s duration. The data have been recorded with a 128-channel amplifier system and digitized at 173.61 Hz sampling frequency and 12-bit A/D resolution.

CHB-MIT Dataset
CHB-MIT is also a benchmark Electroencephalogram database popularly used by many researchers in detection of epileptic-seizure [15]. This data is publicly available in Boston Children Hospital, which is a two-class dataset. This EEG signal database recorded from 23 paediatric subjects. These signals have been recorded with the sample rate of 256 samples per second. For recording the data, 10 - 20 system of EEG electrode positions and nomenclature has been applied.

2.2. Local Binary Pattern

The fundamental LBP operator considers only the eight neighbours of a pixel and it is consisting as a circular format [8]. The basic LBP operator extracts feature from the signal by means of comparing every pixel with its neighbours. This evaluation is based totally on whether the value of the neighbour pixel is large (1) or smaller (0) than the value of each unique central pixel. The results are performed by comparisons of a binary pattern and it’s converted to a decimal value, which is used as a rating of that specific pixel. which is used as a rating of that particular pixel.

2.2.1 1D-Local Binary Pattern

The one-dimensional LBP method, which derived from implementation steps of two-dimensional LBP, was once first of all proposed through Chatlani et al. and Abeg et al. [8, 10] The basic operation of 1D-LBP is sequential analyzes a local of samples in time collecting data. For each data pattern, a binary code is formed by way of thresholding with the value of the specific sample. The formulation of 1D-LBP on a sample is given as:

\[ a_i = s_i - s_c \]  

where:

- \( a_i \) - Decision variable
- \( s_i \) - Amplitude value of the \( i^{th} \) neighbor sample
- \( s_c \) - Amplitude value of the center sample
- \( M \) - Consecutive number of samples considered for finding the LBP value for the center sample and must be odd.
- \( X(p) \) - Bit of value attained by applying the threshold condition.

\[ X(p) = \begin{cases} 1, & p_i \geq 0 \\ 0, & p_i < 0 \end{cases} \]
LBP(z) = \sum_{i=1}^{\left(\frac{M+1}{2}\right)} X(p) \ast 2^i + \sum_{i=\left(\frac{M+1}{2}\right)+1}^{M} X(p) \ast 2^{i-1} \tag{3}

Then LBP value corresponding to \(s_c\) and \(z\) is the sample number.

2.3 Proposed Method

One-dimensional LBP concentrate on the computed & comparison of predefined eight neighbourhood values in the signal [10]. In this paper, two new approaches such as 1D-AaLBP and 1D-AdLBP with CNN as classifier are proposed to classify EEG signals for epileptic seizure detection. These proposed approaches are easy to implement and requires less computation time, and it maintains the structural property of the source data. The details of 1D-AaLBP and 1D-AdLBP feature extraction methods are discussed in the subsequent section. Figure 1 shows the proposed model for the classification of EEG signals the use of these techniques.

2.3.1 Feature Extraction

The transformation methods such as 1D-AaLBP & 1D-AdLBP represents the LBP of a signal. These methods are used to convert a convenient form of the histogram and can be represented as a signal shape. In the histogram, the horizontal axis includes the variation of transformation codes and the vertical axis consists of the number of occurrences of each code. The histogram based graphical shape represents the feature vector of the signal and used for classification.

2.3.2 1D-AaLBP & 1D-AdLBP

1D-AaLBP & 1D-AdLBP is a feature extraction method primarily based on Local Binary Pattern that uses the neighbourhood relationship. This approach has been carried out by considering the neighbouring values of patterns [10]. The different steps of the 1D-AaLBP approach are provided below:

1) Define the no. of neighboring points \(N\) in forward direction.
2) Compute the average value \(A_d\) of \(N\) neighbour points. \(S_t\) is a neighbor signal value.
   \[
   A_d = \frac{1}{N} \sum_{i=0}^{N} S_i \tag{4}
   \]
3) Compute the 1D-AaLBP for each Signal point (Pt), \(S_d\) is average of neighbours value, \(U\) is a unit function
   \[
   U(x) = \begin{cases} 
   1, & x \geq 0 \\
   0, & otherwise
   \end{cases} \tag{5}
   
   \[
   Pr_{AaLBP} = \sum_{i=0}^{N-\left(\frac{N}{2}\right)} U(S_d - A_d) \ast 2^i \tag{6}
   \]
The different steps involved in the 1D-AaLBP are shown in Figure 2.

The different steps of the 1D-AdLBP approach are provided below:

1) Define the no. of neighboring points \( N \) in forward direction.

2) Compute the \( \frac{N}{2} \) difference value \( (D) \) from \( N \) neighbouring points.

\[
D = S_j - S_{j+1}
\]

for \( j = 2*i \) and \( i = 0,1,...,\left(\frac{N}{2} - 1\right) \)

3) Compute the average difference value \( (A_d) \) of \( N \) neighbor points. \( D_i \) is a difference between the neighbor signal value.

\[
A_d = \frac{2}{N} \sum_{i=0}^{N-1} D_i
\]

4) Compute the 1D-AdLBP for each Signal point (Pt), \( U \) is a unit function

\[
U(x) = \begin{cases} 
1, & x \geq 0 \\
0, & \text{otherwise}
\end{cases}
\]
\[ P_{\text{AdLBP}} = \sum_{i=0}^{N-1} U(D_i - A_i) \times 2^i \]  

(11)

The different steps involved in the 1D-AdLBP are shown in Figure 3.

![Diagram of 1D-AdLBP method](image)

(a)

(b)

**Figure 3.** 1D-AdLBP Method; a) neighbours N=8 b) neighbours N=16

2.3.3 Classification

Bayesian Network (BN), Artificial Neural Network (ANN), Support Vector Machine (SVM) and Convolutional Neural Network (CNN) are the popularly used to classify EEG data for detecting epileptic-seizure [16, 17]. CNN is one sort of neural system for handling information that has a realized grid network. For example, time arrangement and frequency arrangement information, which can be thought of as a 1-D network taking examples at normal time interims, and picture information, which can be thought of as a 2-D framework of pixels. Convolutional systems have been very fruitful in certifiable applications. The usage of CNN for signal classification tasks had increased swiftly in recent times because of validated high accuracy achieved through possible by recent network designs and training techniques. CNN’s employ a physically inspired design that varies from fully connected neural networks by using spatial local correlation, creating a net of local connectivity between neurons in end-to-end layers. The use of communal weights in convolutional layers also decreases the system resources, including computer memory required for the network. A general CNN network structure is a feed-forward network, it has three layers namely: (a) convolution layer, (b) pooling layer and (c) fully-connected layer. The proposed deep learning approach using CNN has been illustrated in Table 1.
| S.No | Layer                                      | 1D-AaLBP & 1D-AdLBP | 1D-AaLBP & 1D-AdLBP |
|------|-------------------------------------------|---------------------|---------------------|
| 1    | Input 1D LBP feature vector               | 500 Input data with 512 feature vector (500x512x1) | 500 Input data with 256 feature vector (500x256x1) |
| 2    | Convolution Layer 1                       |                     |                     |
| 3    | Pooling layer 1 (Average)                 |                     |                     |
| 4    | Convolution Layer 2                       |                     |                     |
| 5    | Pooling layer 2 (Max)                     |                     |                     |
| 6    | Convolution Layer 3                       |                     |                     |
| 7    | Pooling layer 3 (Average)                 |                     |                     |
| 8    | Convolution Layer 3                       |                     |                     |
| 9    | Pooling layer 3 (Max)                     |                     |                     |
| 10   | Fully connected (FC) layer 1              | Result of the layer is (2560x1) | Result of the layer is (1280x1) |
| 11   | SoftMax layer 1                           | Reduce (1000x1)     | Reduce (500x1)      |
| 12   | Final Output layer (5 class)              | Reduce (5x1)        | Reduce (5x1)        |

### 3. Experimental results and discussion

#### 3.1. Experimental Results

Benchmark EEG datasets such as Bonn and CHB-MIT are employed to compare the proposed methods with other existing methods for epileptic seizure detection [10, 16, 17]. In our proposed approach, firstly transformation code has been computed for every data. After computing transformation code, histogram is plotted for the computed points. The histogram presents feature-set for the input data and is subsequently applied to classify the EEG signals with different classification techniques. seven experimental cases such as A – E (Bonn), ABCD – E (Bonn), A – D – E (Bonn), B – C – E (Bonn), AB – CD – E (Bonn), A – B – C – D – E (Bonn), A – E (CHB-MIT) and four different machine learning classifiers such as Random Forest (RF), Artificial Neural Network (ANN), SVM and CNN are applied in this work. Based on the experiments conducted, it is found that the highest accuracy is achieved when the neighbouring points are set to 8&16 and the length of the feature-set is 256&512. The performance
measures in terms of classification accuracy of 1D–AaLBP, 1D–AdLBP and Combined 1D–AaLBP & 1D-AdLBP methods with neighbouring points (8,16) based on various experimental cases are presented in Figure 4, 5 & 6.

**Figure 4.** Comparison of performance measures of the proposed 1D-AaLBP method with various classification methods

**Figure 5.** Comparison of performance measures of the proposed 1D-AdLBP method with various classification methods
Figure 6. Comparison of performance measures of combined 1D-AaLBP & 1D-AdLBP method with various classification methods.

The proposed 1D-AaLBP, 1D-AdLBP and Combined 1D-AaLBP & 1D-AdLBP methods with CNN classifier achieves better results in terms of classification accuracy. The performance measures such as sensitivity, specificity, and classification accuracy along with standard deviation for different neighboring points N=8, N=16 are presented in Figure 7 & 8.

Figure 7. Comparison of performance measures of 1D–AaLBP, 1D–AdLBP and Combined 1D–AaLBP & 1D–AdLBP methods with CNN classifier (N=8)
For real-time monitoring, the proposed 1D-AaLBP, 1D-AdLBP and Combined 1D–AaLBP & 1D-AdLBP methods can be effectively applied and which are computationally efficient with different classes. The mean execution time is computed with the proposed method with neighboring point N=8, N=16 and the results are shown in Figure 9 & 10.

Figure 8. Comparison of performance measures of 1D–AaLBP, 1D–AdLBP and Combined 1D–AaLBP & 1D-AdLBP methods with CNN classifier (N=16)

Figure 9. Comparison of Execution time (in seconds) of combined 1D–AaLBP & 1D-AdLBP method for different classes (N=8)
Figure 10. Comparison of Execution time (in seconds) of combined 1D–AaLBP & 1D-AdLBP methods with different classes (N=16)

The neighboring point of N=8 & N=16 is compared with the proposed method of Combined 1D–AaLBP & 1D-AdLBP and CNN classifier. The Combined 1D–AaLBP & 1D-AdLBP N=16 achieved better classification accuracy for different experimental cases which are shown in Figure 11.

Figure 11. Comparison of Classification Accuracy of combined 1D–AaLBP & 1D-AdLBP methods for different classes

3.2 Results and Discussion
The proposed 1D–AaLBP, 1D–AdLBP and Combined 1D-AaLBP & 1D-AdLBP with CNN methods achieves better performance results in terms of classification accuracy, sensitivity and specificity for most of the experimental cases over the existing classifiers such as RF, ANN and SVM, which are presented in Figures 4 to 8. For cases 1 to 7, the Combined 1D-AaLBP & 1D-AdLBP achieved highest accuracy on 10 fold cross-validation method with 50 runs. High classification accuracy is achieved using 1D–AaLBP, 1D–AdLBP methods when experimented with CNN classifier. Minimal execution time for classification of EEG signals using various classifiers were achieved. CNN classifier took minimal time for training and its accuracy for classification was better than other existing classifiers. It is concluded that the proposed Combined 1D-AaLBP & 1D-AdLBP with CNN method produced significant classification accuracy with neighbouring point N=16 over N=8, and the results are presented in Figure 10 & 11.

4. Conclusion
In this work, the three efficient feature extraction methods such as 1D-AaLBP, 1D-AdLBP and Combined 1D-AaLBP & AdLBP have been proposed for extracting features from EEG signals. For classification, Convolutional Neural Network (CNN) have been employed. The proposed feature extraction methods are experimentally simple and easy to implement and it also provides better performances. The efficiency of the proposed methods have been validated with the benchmark EEG datasets namely Bonn and CHB-MIT. Five different experimental cases have been tested to validate the
effectiveness of the proposed approaches. The maximum classification accuracies (in %) such as 99.65, 99.24, 99.10, 98.88, 99.11 and 98.80 are achieved with combined 1D-AaLBP & AdLBP for various experimental cases, such as A – E (Bonn), ABCD – E (Bonn), A – D – E (Bonn), B – C – E (Bonn), AB – CD – E (Bonn), A – B – C – D – E (Bonn), A – E (CHB-MIT) respectively. Moreover, the computation time also very low when compared to other classifiers. The future work will be on implementing this technique for real-time epileptic seizure detection because of its high performance and low computational time are suitable for real-time signal processing.

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