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Schizophrenia Detection in Adolescents from EEG Signals using Symmetrically weighted Local Binary Patterns

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Abstract—**Schizophrenia is one of the most complex of all mental diseases. In this paper, we propose a symmetrically weighted local binary patterns (SLBP)-based automated approach for detection of schizophrenia in adolescents from electroencephalogram (EEG) signals. We extract SLBP-based histogram features from each of the EEG channels. These features are given to a correlation-based feature selection algorithm to get reduced feature vector length. Finally, the feature vector thus obtained is given to LogitBoost classifier to discriminate between schizophrenia and healthy EEG signals.**

The results validated on the publicly available database suggest that the SLBP effectively characterize the changes in EEG signals and are helpful for the classification of schizophrenia and healthy EEG signals with a classification accuracy of 91.66%. In addition, our approach has provided better results than the recently proposed approaches in schizophrenia detection.

I. Introduction

Schizophrenia is a chronic, severe mental disorder affecting above 20 million people globally [1]. Schizophrenia is characterized by irregularities in thinking, cognitive abilities, and often perturbation. The common symptoms of schizophrenia are disorganized speech, hallucinations, delusions, agitation. The chances of early mortality in patients with schizophrenia are 2-3% more likely than the other people [2]. This mental illness is correlated with significant disability in doing work and affects the performance of educational and occupational tasks. It is noteworthy that adolescent-onset psychosis produces worse outcomes of disorder when compared to adult-onset schizophrenia [3]. Though it is a treatable disease, 90% of the low and middle-income countries with schizophrenia are untreated because of a lack of awareness of mental health services. Worldwide more than 60% of people are not receiving timely action and care [1].

Early treatment may help in reducing long-term complications and can improve mental stability. Generally, the treatment is based on the Psychiatric evaluation, where the clinician observes the candidate, asks about thoughts, delusions, hallucinations, and any other related questionnaire. It is one of the subjective analyses, and a patient may resist sharing his experience with an unknown person. Therefore, a clinically authenticated procedure is very much required. Investigating mental disorders using physiological signals in an automated way is one of the reliable solutions [4]. Automated diagnosis also reduces tedious manual inspection.

A few works explored electrocardiogram (ECG), and electromyogram (EMG) signals to characterize schizophrenia [5]. Nevertheless, the performance of these works is limited because of less correlation between these signals and schizophrenia. The significant clinical essence of the electroencephalogram (EEG) in psychiatry makes it a valuable investigation tool in recognizing schizophrenia [4].

In the last few decades, several researchers have focused their efforts on detecting schizophrenia in adults using EEG signals [4-6]. Even though schizophrenia in adolescents is alarming, only a few works have concentrated on identifying schizophrenia in adolescents [7-9]. Therefore, we aim to develop an effective approach for schizophrenia detection in adolescents.

In [7], the authors proposed a method based on epsilon-complexity of continuous functions to estimate the multichannel EEG signals in different mental states. Later, the estimated coefficients are given to a random forest classifier to classify adolescent schizophrenia patients from healthy patients. A deep learning (CNN) based schizophrenia classification method is proposed in [8]. In [9], the authors proposed a multidomain-based feature extraction with a blend of CNN for adolescent schizophrenia classification. Most of the existing methods relied on either time-frequency domain-based feature extraction from EEG signals or deep learning-based algorithms. In contrary to the existing works, we propose a local descriptor-based approach for schizophrenia detection in adolescents.

One-dimensional local binary pattern (1D-LBP) is a local descriptor that captures local changes by performing simple comparison operations in the local neighborhood of a sample.1D-LBP, and its variants have been found to be very effective in signal classification tasks involving EMG, ECG, speech, and EEG signals [10-13]. Despite their evident advantages, local descriptors have not been explored for schizophrenia detection. In this paper, we propose a symmetrically weighted local binary patterns-based approach for schizophrenia detection.

The rest of the paper is organized as follows: Section II describes the Dataset employed and the proposed approach for schizophrenia detection. Section III presents experimental results, and conclusions are drawn in Section IV.

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II. METHODOLOGY

A. Dataset

In this work, we employ the EEG dataset of adolescents available on the Moscow State University website [14]. This data comprises EEG data corresponding to 84 adolescents. Out of 84 subjects, 39 are healthy adolescents, and the remaining 45 are adolescents with schizophrenic disorders. The mean age of the adolescents is 12.3 years. The EEG signals were recorded when the subjects are wakefully relaxed and eyes are kept closed. A 16 electrode EEG system with a sampling rate of 128 samples per second is used to acquire the data. Each EEG channel is of one minute length. More details of the data can be found in [15].

B. Proposed approach

The block diagram of the proposed SLBP-based approach for schizophrenia detection is depicted in Fig. 1. Firstly, SLBP-based histogram features are computed from each of the 16 channel EEG signals. These features are given to the correlation-based feature selection approach to select the prominent features and reduce the length of the feature vector. Finally, the reduced feature vector is subjected to the LogitBoost classifier for the classification of schizophrenia and healthy EEG signals. This approach is further detailed below.

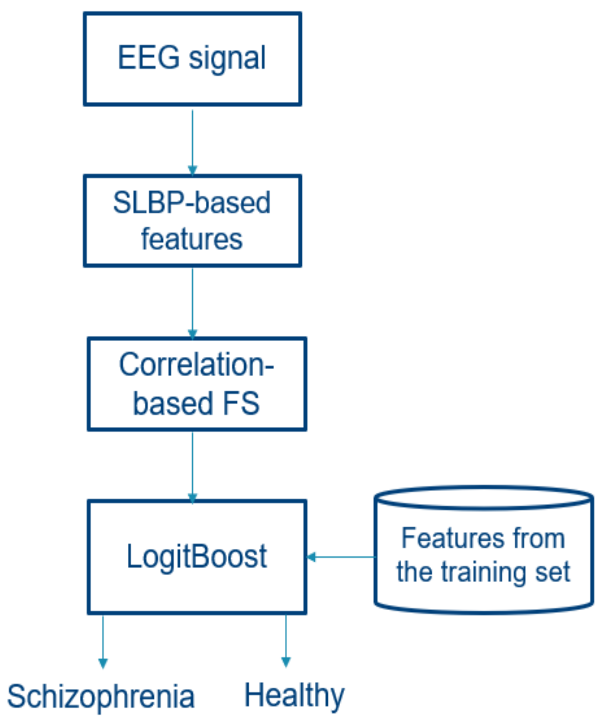

Fig.1. Block diagram of the SLBP-based approach for detection of schizophrenia

Symmetrically weighted local binary pattern: SLBP [16] is a variant of 1D-LBP, initially proposed for sleep apnea detection. The significant advantage of the SLBP over 1D-LBP is its reduced feature vector length. SLBP requires a histogram of length 31, whereas 1D-LBP requires a histogram of length 256 for its representation. Like 1D-LBP, SLBP computes binary patterns by thresholding right and left neighbors with a center sample. However, as opposed to 1D-LBP, the generated binary information is encoded into decimal value using the symmetric weighting scheme. Mathematical equations involved in SLBP-based features are given below [16].

$$SLBP_{LHS}(s[n]) = \sum_{m=0}^{L-1} f(s[n+m-L] - s[n])2^{L-1-m} \quad (1)$$

$$SLBP_{RHS}(s[n]) = \sum_{m=0}^{L-1} f(s[n+m+1] - s[n])2^{L} \quad (2)$$

$$SLBP\ (s[n]) = SLBP_{LHS}(s[n]) + SLBP_{RHS}(s[n]) \quad (3)$$

where $s[n]$ represents the current sample of the signal, L is the neighborhood size considered on the either side of the current sample and thresholding function f is defined as

$$f(x) = \begin{cases} -0, & x < 0 \\ 1, & x \geq 0 \end{cases}$$

An example of SLBP computation can be found in [16]. The above equations are used to compute the SLBP sequence of a signal. Typically, a histogram of size 31, extracted from the SLBP sequence, is used as a feature vector. In our experiments, the neighborhood length L is fixed to 4. Specifically, the current sample is compared with 4 neighboring samples on the either side.

In our approach, SLBP-based histograms are extracted from each of the EEG channels. As there are 16 channels, histograms extracted from each of these channels are concatenated to get a feature vector of length 496.

Correlation-based feature selection: Correlation-based feature selection (CFS) ranks the features based on feature-feature correlation and feature-classification correlation [17]. In this work, the SLBP-based histogram of length 496 extracted from 16-channel EEG system is given to CFS to reduce the feature vector length and to select the prominent features for schizophrenia detection.

LogitBoost Classifier: The final vector obtained from CFS is given to LogitBoost [18] meta classifier with a random forest as a base learner to classify EEG signals into healthy and schizophrenia.

III. RESULTS AND DISCUSSION

In this section, the simulation results of the proposed work, as shown in Fig. 1, are presented. The SLBP-based feature vector of length 496 extracted from a 16-channel EEG system is given to CFS for feature reduction. The CFS algorithm has selected 29 features from 496 features. These 29 features are fed to LogitBoost classifier for schizophrenia detection.

In order to evaluate the performance of the SLBP-based approach for schizophrenia detection in adolescents, we have employed a 10-fold cross-validation approach. The performance is measured in terms of classification accuracy, specificity, and sensitivity [8]. Accuracy determines the total number of correctly classified instances. Sensitivity and specificity determines the ability of identifying schizophrenia subjects, and healthy subjects, respectively.

The proposed feature extraction is implemented using MATLAB 2016b[R], and the feature selection and classification tasks are performed using the software WEKA 3.9 version. After extracting a feature vector of length 496 from 16 channel EEG system, these features were given to CFS for feature reduction. . In our experiments, we have computed the mean of performance metrics obtained using 10-fold cross validation. The results of our approach are shown in TABLE 1.

TABLE I. PERFORMANCE EVALUATION OF THE SLBP-BASED APPROACH FOR SCHIZOPHRENIA DETECTION

Feature Selection (FS)	*Classification Accuracy (%)*	*Specificity (%)*	*Sensitivity (%)*	*Feature vector length*
Without FS	86.90	87.18	86.67	496
CFS	91.66	89.74	93.33	29

From TABLE 1, it can be noticed that the SLBP-based approach detects schizophrenia in adolescents with an accuracy of 86.90%, which suggests that SLBP-based features effectively detect schizophrenia from EEG signals. However, the length of the feature vector is 496, which is a drawback. When CFS is employed, the length of the feature vector has been reduced to 29. Furthermore, it can be observed that the performance has been enhanced significantly when the CFS algorithm is employed. More specifically, the classification accuracy is improved by 4.76 points. It shows the efficacy of the CFS algorithm in identifying discriminative features from high-dimensional feature space.

TABLE II. PERFORMANCE COMPARISON WITH EXISTING APPROACHES

Ref. No.	*Number of subjects*	*Method*	*Performance measures (%)*
[6]	Healthy: 53, Schizophrenia: 48	MCCA+SVM	Accuracy: 74
[7]	Healthy: 39, Schizophrenia: 45	Epsilon-complexity function+RF	Accuracy: 83.6
[8]	Healthy: 39, Schizophrenia: 45	Pearson Correlation Coefficient + CNN	Accuracy: 90, Sensitivity: 90, Specificity: 90
[9]	Healthy: 39, Schizophrenia: 45	Time and frequency domain features+ CNN	Accuracy: 91.69
This work	Healthy: 39, Schizophrenia: 45	SLBP+Logitboost	Accuracy: 91.66, Sensitivity: 93.33, Specificity:89.74

The performance comparison of the proposed approach with existing works in schizophrenia detection from EEG signals is shown in TABLE II. From TABLE II, it is evident that our proposed approach yielded better performance than the approaches in [6-8]. The approach in [9] has provided marginally better classification accuracy than the proposed approach. However, the approach in [9] employs features extracted from the time and frequency domain, and the dimension is very high. In our case, the feature vector length is only 29. In addition, they have employed CNN for classification, which requires expensive GPUs.

The key advantage of our approach is SLBP-based feature extraction. The SLBP-based feature extraction is computationally simple, and it involves only basic operations. In addition, the length of the feature vector is less. On the other hand, the disadvantage of our approach is that the performance is evaluated only on one dataset. The proposed approach should be validated on a larger dataset before using it for clinical purposes. We want to take up this challenge as a part of our future work.

IV. CONCLUSION

In this work, we presented an SLBP-based automated approach for schizophrenia detection in adolescents from EEG signals. In addition, the CFS algorithm is employed to reduce the feature vector length. Our experimental results suggest that the CFS algorithm reduced the feature vector length and improved the performance of the approach significantly. Specifically, the SLBP-based approach achieved an accuracy of 91.66%for the classification of healthy and schizophrenia EEG signals. Also, it outperformed many of the existing approaches in schizophrenia detection from EEG signals.

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