Biophysics

AIMS Biophysics, 10(3): 347–371.
DOI: 10.3934/biophy.2023021
Received: 04 April 2023
Revised: 23 July 2023
Accepted: 25 July 2023
Published: 20 September 2023

http://www.aimspress.com/journal/biophysics

Research article

Multi-class EEG signal classification with statistical binary pattern synergic network for schizophrenia severity diagnosis

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Abstract: Electroencephalography (EEG) is a widely used medical procedure that helps to identify abnormalities in brain wave patterns and measures the electrical activity of the brain. The EEG signal comprises different features that need to be distinguished based on a specified property to exhibit recognizable measures and functional components that are then used to evaluate the pattern in the EEG signal. Through extraction, feature loss is minimized with the embedded signal information. Additionally, resources are minimized to compute the vast range of data accurately. It is necessary to minimize the information processing cost and implementation complexity to improve the information compression. Currently, different methods are being implemented for feature extraction in the EEG signal. The existing methods are subjected to different detection schemes that effectively stimulate the brain signal with the interface for medical rehabilitation and diagnosis. Schizophrenia is a mental disorder that affects the individual's reality abnormally. This paper proposes a statistical local binary pattern (SLBP) technique for feature extraction in EEG signals. The proposed SLBP model uses statistical features to compute EEG signal characteristics. Using Local Binary Pattern with proposed SLBP model texture based on a labeling signal with an estimation of the neighborhood in signal with binary search operation. The classification is performed for the earlier-prediction shizophrenia stage, either mild or severe. The analysis is performed considering three classes, i.e., normal, mild, and severe. The simulation results show that the proposed SLBP model achieved a classification accuracy of 98%, which is ~12% higher than the state-of-the-art methods.

Keywords: electroencephalogram; statistical features; local binary pattern; classification; synergic network

1. Introduction

In medical diagnosis, numerous electroencephalography (EEG) signals are generated, and neurophysicians utilize these signals to detect the presence or absence of schizophrenia and provide accurate diagnoses [1]. With the ever-increasing database size, the prediction rate and classification performance are the main issues for schizophrenia detection methods. One of the primitive solutions is to use optimization methods to enhance classification performance. Because of the reasons mentioned above, it is believed that an automated schizophrenia detection method is required for faster diagnosis and also to handle the more extensive EEG database [2]. The main aim of this research was to build an efficient model of schizophrenia classification by using various features selected from the input EEG signals to realize the system's high performance.

When trying to diagnose schizophrenia, EEG is a valuable tool. Since some methods rely on human processes, we need an effective automated strategy for segmenting the signals associated with schizophrenia, including focal, non-focal, pre-ictal, interictal, and ictal signals, from the database [3].

- Fewer features can be retrieved from the signals if there are not enough signals in the database. Poor signal categorization results from having a small database.
- The EEG classification system's approach did not improve classification performance (as measured by the error rate) on a large dataset. The best function available in the system can reduce the error rate to a minimum.
- Some algorithms have achieved higher classification in detecting schizophrenia but can only be classified from a database of uniform patterns. However, most EEG signal databases are not available in this format.

The EEG is the most often used biological signal signal-obtaining system in neurology practices. However, several others also contribute to therapeutic applications. Nearly one percent of the world's population suffers from schizophrenia, and EEG recordings of brain activity are used to diagnose the disorder and predict the patient's behavior [4]. Humans have a naturally significant, if not always exact, ability to distinguish between focal and non-focal signals. Classifying focal and non-focal EEG signals manually takes longer and can only be used with limited EEG datasets. As a result, researchers have taken notice of an autonomous schizophrenia classification system with several potential uses [5].

Researchers working on autonomous schizophrenia classification systems have difficulty gathering noise-free data. The majority of signals come from EEG devices, and these EEG signals primarily include impulse noise and machinery noise (electrical and mechanical noise). When using semi-supervised methods with acquired EEG signals, the semantic gap between feature values is maximized, resulting in a low classification rate. The performance of binary machine learning classifiers in terms of classification rate suffers significantly if the sample size in the training set is small [6].

Artifacts are unwanted signals which degrade the biological signal's quality. The major work in EEG signal monitoring is artifact elimination and recognition. The schizophrenia observation is inhibited by extra-physiological and physiological artifacts [7]. The patient-associated artifacts are physiological (e.g., eye movements, cardiac activity, muscle activity, and sweating), and the technical artifacts are extra-physiological (e.g., electrode popping and the 50/60 Hz artifact), which are difficult to handle. A few tools, such as electromyography, electroocculography, and electrocardiography, are used to identify artifacts, i.e., myogenic, cardiac, and ocular artifacts [8].

A common type of physiological artifacts are those derived from eye movement. It is a significant source of EEG signals because eye movements cause an adjustment in the electric field that encompasses the eye and correspondingly significantly distort the electric fields over the scalp [9]. Eye blinks are another essential artifact source that generates high-amplitude EEG signals. EEG data are regularly corrupted by eye blink artifacts, which occur due to the closing and opening of eyelids. The EEG records must be artifact-free to examine the EEG signal for diagnosis [10].

A neurological disorder is a brain disorder that affects the brain nerves throughout the body and spinal cord and it arises due to biochemical, structural, or electrical abnormalities. Many of the neurological disorders are common with a few being exceptional. A comprehensive neurological investigation is performed neuropsychologists and dexterous neurologists using to assess such disorders [11]. The World Health Organization projected that these disorders affect over 1 billion people. This number is predicted to grow with the rise in population, as these disorders are becoming a serious risk to public health. These disorders can interfere with daily life activities, medication, operations performed by neurosurgeons, physiotherapy, neurorehabilitation-related pain management, and preventative measures [12]. Symptoms associated with these disorders are sensation loss, poor correlation, muscle weakness, confusion, schizophrenia, altered consciousness levels, and paralysis. Analysts and policymakers suggested that the seriousness of a disease depends on the mortality statistics based on the disease control programs [13].

This study aimed to develop an efficient and accurate method for diagnosing schizophrenia based on EEG signals. Schizophrenia is a mental disorder that affects an individual's perception of reality, and EEG signals provide valuable information for its diagnosis. The research addresses several key challenges in schizophrenia detection. First, as the size of the EEG database continues to grow, there is a need for faster and more accurate prediction and classification methods. The researchers aimed to develop an automated schizophrenia detection method to handle large EEG databases and provide faster diagnoses. Second, extracting relevant features from EEG signals is crucial for accurate classification. The proposed method utilizes statistical local binary patterns (SLBP) for feature extraction and it considers the statistical features of EEG signals. By using an SLBP, the researchers aimed to capture the distinctive characteristics of EEG signals associated with schizophrenia. Furthermore, the research classifies EEG signals into three categories: normal, mild schizophrenia, and severe schizophrenia. This multi-class classification allows for the earlier prediction of schizophrenia stages; it also facilitates appropriate medical intervention.

1. The paper introduces the SLBP model as a novel approach for feature extraction from and classification of EEG signals. The SLBP model incorporates statistical-based feature estimation techniques, such as Electromagnetic Pulse (EMP) and variational mode decomposition (VMD), to capture relevant characteristics of EEG signals associated with schizophrenia.
2. The proposed SLBP model is applied in a synergic mode to classify EEG signal characteristics. The classification is performed based on the consideration of three classes: normal, mild schizophrenia, and severe schizophrenia. This allows for the earlier prediction of schizophrenia stages, which can aid in timely medical intervention and treatment planning.
3. The simulation results presented in the paper demonstrate that the proposed SLBP model

achieves a classification accuracy of 98%. This accuracy is approximately 12% higher than conventional classification techniques for schizophrenia diagnosis. The higher accuracy highlights the effectiveness of the SLBP model in accurately identifying and classifying EEG signals related to schizophrenia severity.

Here, we propose an SLBP model for the feature extraction and classification tasks for EEG signal processing, and an overall summary is presented to describe how the proposed SLBP model preprocesses the data and computes the features of the EEG signal. The SLBP techniques perform the feature extraction in consideration of the Electromagnetic Pulse (EMP) and by applying VMD to the features in the EEG signal bia statistical features estimation. The local binary pattern is applied to evaluate the signal attributes after estimating the statistical-basic features. Finally, the developed SLBP model is applied over the synergic mode to classify the EEG signal characteristics. The classification is performed based on the consideration of normal, mild schizophrenia, and severe schizophrenia. The simulation results show that the proposed SLBP model achieved an accuracy of 98%, which is ~12% higher than that achieved by the conventional classification techniques.

2. Related works

In [14], they developed a competitive swam dragonfly algorithm (CSDA) model for classifying EEG signals. The proposed CSDA model computes the EEG signal artifacts by estimating them in the preprocessing phase. With the imperative feature extraction model, spectral-based features are computed based on the amplitude spectrum, spread of spectrum, power spectral density, and log power band. Also, the model computes the statistical features considering of the skewness, entropy, and kurtosis. The data for further processing is computed by performing data augmentation by implementing a deep residual network (DRN) to classify EEG motor signals. The DRN mode uses the CSDA to perform training to realize an integrated optimization model, such as one based on swarm optimization and dragonfly algorithm. The multi-class dataset is computed to determine motor signal training and testing for the multi-class dataset. The CSDA model achieved higher specificity, accuracy, and sensitivity values of 91.9%, 91.6%, and 92.3%, respectively.

In [15], they considered the encoding of EEG signal data by employing a 2D-kernel CNN model with the data preprocessing. The examination considers the different computation fields' differences of Gramian angular, Markov transition fields, recurrence plots, and summation fields. The model's performance is comparatively examined with a selection of CNN features with an exhibition of BCI system performance on cross-subject data with short time intervals.

In [16], they present a multi-layer twin support vector machine (MTSVM) comprising a wavelet transform (WT). The proposed MTSVM model also incorporates the phase space reconstruction (PSR) singular value decomposition (SVD) model. The WT-PSR-SVD model evaluates the EEG signal features with the decomposition of the EEG signal for the high-dimensional space reconstruction for the PSR through reflection of WDSs EEG signal. The traditional multi-layer SVM and WPS-MTSVM models were compared regarding their ability to learn features. The experimental results demonstrated that the proposed WPS-MTSVM model exhibits improved performance relative to that of the WT-SVD model in terms of effective EEG signal classification.

In [17] aimed to evaluate the issues in the automatic classification of EEG signals for robust performance characteristics. The automatic classification model performs a clustering process by computing features with a probability distribution. The distribution probability is computed based on considering the EEG signal with six stages with the segmentation of minor epochs in 30 seconds with the classification of 60 sub-segments. The discrete wavelet transform comprises the five levels for the coefficient approximation. Through k-means algorithm clustering, the wavelet coefficient is computed at each cluster level. The features in the EEG signal are extracted based on the wavelet coefficient-based probability distribution function. The features are extracted based on the most miniature square support vector machine for the identification of sleep stages. The performance of the proposed model is compared with the existing methods with an average accuracy rate of 97.4%. The classification analysis expressed that the proposed model exhibits an improved diagnosis for the mental disorder.

In [18], they proposed a hybrid neural network model for motor signal classification for end-to-end multi-branch communication. The input signal is classified into four bands with the estimation of a motor signal. EEG features are identified and estimated by introducing a bidirectional gated recurrent unit (BGRU). The EEG data is processed and classified based on the estimation of complexity in the EEG data. The proposed model exhibits improved augmentation in the frequency domain of the segmentation. Both the BCI IV 2a and the High Gamma datasets are considered during the decoding model's performance analysis. Values of 86.15% and 95.04% are displayed by the proposed multi-branch hybrid neural network (MBHNN) for the two datasets, respectively.

In [19], it aimed to increase the real-time BCI application for binary and multiclass classification. The EEG signal is computed based on estimating the nonstationary effect in the EEG signal to achieve the accuracy value of 50% for the raw data with a preprocessing value of 90% with binary and multiclass values of 28% and 78%. The filtered signal is calculated using an automated filtering procedure employing an optimized since cosine algorithm (SCA) to assess the beta wave's features in an EEG recording. For the UCI and PhysioNet datasets, implementing the light gradient boosting machine (LGBM) classifier eliminates correlated features based on the extracted features, exhibiting 99% and 95% accuracy, respectively. The model uses the 14 channels to compute feature values of 70% and 98% with improved robustness and prediction quality.

In [20], classification using a machine learning model for human emotions with the extracted features of EEG. The developed model is evaluated with the database for emotion analysis using the physiological signal (DEAP) dataset, considering the peripheral biological EEG dataset. The dataset comprises 32 subjects with min-long video sequences. Every video clip is estimated based on the valence, arousal, and Dominance with the minimized EEG signal with the frontal electrode. The proposed model achieves an accuracy value of 92.5%, and the KNN model achieves an accuracy of 90% and 90% for KNN and Support Vector Machine (SVM), respectively.

In [21], they proposed a graph embedding method for the feature level performance in EEGNet level. The proposed EEGNet uses the time-domain features to convene EEG signals using electrodes. The conceptualized graph filter-based adjacent matrix performs graph convolution for the time-domain features in topology form. The process comprises the multi-order embedding graph with the adjacency matric connecting the different brain networks to perform classification. The experimental analysis expressed that the proposed model performance is evaluated with the BCICIV-2a and High Gamma datasets, providing classification accuracy of 79.57% and 96.02%. The results demonstrated that the proposed model is effective for the feature graph embedding model.

In [22], an EEG signal feature selection and classification was developed using a predator algorithm. The prediction is performed with the inter-subjects and spontaneous prediction for extracting 1792 features in time, frequency, and nonlinear features. The predator algorithm extracts the optimal features in the subset with consideration of hyperparameters for the prediction. The model's performance exhibits a prediction accuracy of 79% for the selection and classification integrated with the metaheuristics algorithm.

In [23], it is described that SchizoNET is a model that combines a convolutional neural network (CNN) with the Margenau-Hill time-frequency distribution (MH-TFD). Automatic SZ detection relies heavily on the time-frequency domain. Using the time-frequency domain, MH-TFD records the immediate details of EEG signals. The created CNN model is given two-dimensional plots of the time-frequency amplitude. SchizoNET is trained on three independent public SZ datasets and validated with holdout, five-fold, and ten-fold cross-validation methods. On Datasets 1, 2, and 3, the suggested model had an accuracy of 97.4%, 99.74%, and 96.35%, respectively.

In [24], this research explores the use of physiological signals for the automated diagnosis of developmental and mental diseases. The advantages, future directions, and challenges of previously published works on children's mental diseases are also discussed in-depth, along with their relevance to the field as a whole. The Authors have provided a thorough description of the dataset, validation methods, extracted features, and decision-making models. Open issues on signal or availability, uncertainty, explainability, and hardware implementation resources are all part of the hurdles and potential future directions for signal analysis and machine or deep learning models.

In [25], an automated model is created by combining resilient variational mode decomposition (RVMD) with an optimized extreme learning machine (OELM) classifier for the correct interpretation of EEG signals during SCZ. Typical VMD has issues with noise in the mode-generating process, mode duplication, insufficient mode segmentation, and mode discarding. By automatically selecting a quadratic penalty factor and a fixed number of modes (L), RVMD gets rid of these problems. The OELM classifier's hyperparameters (HPM) are selected automatically to avoid overfitting and underfitting. Whale optimization is used to determine the values for RVMD and L and HPM and OELM, two of the classifier's parameters. The OELM classifier optimizes the root-mean-square error, whereas RVMD optimizes the accuracy of mode classification. To detect SCZ, the EEG signals of three conditions, as they performed fundamental sensory tasks, were evaluated.

In [26], the authors offer an automatic signal decomposition and classification approach that can distinguish between SZ and control EEG data. To select the most discriminative channel, the Fisher score approach is applied. The root mean square error in decomposing EEG signals is minimized using the grey wolf optimization (GWO) algorithm, which led to the development of the flexible tunable Q wavelet transform (F-TQWT). From the subbands created adaptively, five features are picked using the Kruskal-Wallis test. The flexible least square support vector machine (F-LSSVM) classifier inputs the feature matrix. Using the GWO technique, we optimize the hyper-parameters and kernel of the classifier to get the highest possible accuracy in each subband.

In [27], the authors offer a methodology design utilizing the empirical mode decomposition (EMD) technique for SZ diagnosis from EEG data, which is particularly well-suited to dealing with such signals' nonstationary and nonlinear nature. In this investigation, the EMD method breaks down each EEG signal into a set of intrinsic mode functions (IMFs), which are then used to derive a set of twenty-two statistical characteristics/features. The Kruskal-Wallis test is used to determine which five characteristics are most important. The acquired feature set is put through its paces through a battery of well-known classifiers on an SZ EEG dataset to gauge its efficacy. The ensemble bagged tree outperformed the other classifiers by a wide margin, with a SZ accuracy of 93.21% and an IMF 2 accuracy of 89.59%.

In [28], an automated identification of SZ is proposed utilizing a mixture of time-frequency analysis and convolutional neural network (CNN) to overcome the drawbacks of feature extraction-based approaches. Normal participants and SZ patients are differentiated by analyzing three press-button tasks. Scalograms, spectrograms, and SPWVD-based time-frequency representation (TFR) plots are generated from the EEG data after processing with continuous wavelet transform, short-time Fourier transform, and SPWVD approaches. Pretrained versions of AlexNet, VGG16, ResNet50, and CNN are given these 2-D plots.

In [29], the highly nonstationary electroencephalogram signals are decomposed into modes in a Fourier spectrum using empirical wavelet transformation. The modes extract linear and nonlinear aspects in the time domain. The Kruskal-Wallis test is used to select highly discriminatory characteristics. Both healthy people and people with schizophrenia are classified using various classification methods. Different performance characteristics, such as accuracy, sensitivity, precision, and specificity, are analyzed to determine the system's efficacy.

In [30], the authors propose a multivariate analysis of the EEG signal for the diagnosis of Schizophrenia. Intrinsic mode functions (IMF) are derived from the EEG data by multivariate empirical mode decomposition (MEMD). The entropy of an IMF signal provides a measure of how unpredictable the signal is. Five different types of entropy are applied to the IMF signal for analysis: approximate entropy, sample entropy, permutation entropy, spectrum entropy, and singular value decomposition entropy. There was a statistically significant distinction between the schizophrenics and the controls on entropy measures. The entropy values of the IMF signal are used to train a number of SoA machine learning classifiers; however, the support vector machine based on the radial basis function (SVM-RBF) had the maximum accuracy and F1-score for the 95 features.

In [31], utilizing a publicly available EEG signal data set, an automated model for detecting schizophrenia is provided utilizing a cyclic group of prime order with a modulus 17 operator. The proposed feature extractor is the cyclic group of the prime order pattern (CGP17Pat). The proposed CGP17Pat is implemented in a new multilevel feature extraction model. To categorize the characteristics, we utilized the k-nearest neighbors (kNN) algorithm, and we used 10-fold cross-validation and leave-one-subject-out (LOSO) validation to zero in on a truly unique feature. In the final phase, we used iterative hard majority voting to acquire channel-wise results, and then we calculated the overall outcomes.

In [32], the authors provide a unique automated schizophrenia detection model that uses EEG signals and is based on the Collatz conjecture. This model's goals are twofold: to demonstrate the power of conjecture-based structure in generating features and to provide a highly accurate EEG-based schizophrenia diagnosis model that requires minimal patient input and processing time. Our concept consists of three distinct phases. Using the Collatz conjecture, a novel function for generating features is introduced and named the Collatz pattern. The Collatz pattern and the maximum absolute pooling decomposer are combined to form a novel multilevel feature generation approach used to extract both low-level and high-level features. (ii) The features that are considered clinically relevant are subjected to iterative neighborhood component analysis (INCA). (iii) A k nearest neighbors (KNN) classifier automatically detects SZ based on the selected features.

In [33], this work investigates a method known as VMD-HT, which combines VMD with the Hilbert transform to decipher EEG data. The AMF absolute values were utilized to generate forty-one statistical parameters, which were then classified using the explainable boosted machine

(EBM) model. We employ statistical analysis and performance measures to guarantee the model's readability. We identified the most essential characteristics, neural circuits, and psychological processes by contrasting the glass-box and black-box approaches. The model's local and global explainability have been visualized using local interpretable model-agnostic explanations (LIME), shapley additive explanations (SHAP), partial dependence plots (PDP), and Morris sensitivity. This is the only study we know about that investigates the explainability of the model prediction in ADHD diagnosis, and it focuses on youngsters.

In [34], the authors present a method for detecting sleepiness using variational nonlinear chirp mode decomposition (VNCMD). The signal is broken down into time- and frequency-specific bands using VNCMD. EEG signals are sampled regularly and analyzed for various linear and nonlinear properties. The Kruskal-Wallis test is utilized to pick the primary characteristics. Various classifiers are used to categorize highly discriminating features. The efficiency of the system is measured in several ways. Finally, the performance of the suggested approach is assessed by contrasting it with other methods employing the same dataset.

The research gaps identified in the mentioned papers revolve around the need for further exploration and improvement in the classification of EEG signals. While these studies' proposed models and algorithms show promising results, several areas require attention. First, there is a need to evaluate the generalization and robustness of the proposed models across different datasets and real-world scenarios. This would help assess the models' applicability in diverse contexts and their ability to handle variations in EEG data. Second, there is a need to investigate the performance of the proposed models under noisy or incomplete EEG signals, as these issues are commonly encountered in practical settings. Third, there is a need for comparative analyses that evaluate the performance of different models and algorithms, allowing for a better understanding of their strengths and weaknesses. Such comparisons can guide researchers in selecting the most suitable approaches for specific EEG classification tasks. Finally, considering the increasing concern about adversarial attacks on EEG-based systems, there is a need for further research on the development and evaluation of defense mechanisms to enhance the security and reliability of EEG-based applications. Addressing these research gaps would contribute to advancing EEG signal classification techniques and their practical implementation in various domains.

3. Proposed statistical EEG feature extraction

The developed SLBP model focused on detecting the different stages of the Schizophrenia with the elimination of Ocular defects (OD). Initially, the signal acquired is converted in the data format and converted in the image data. The proposed SLBP model estimates the EMP and VMD in the signal for the accurate diagnosis. The EEG signal is subjected to artifacts that affect the overall process in terms of size, and it's complicated to predict diseases accurately.

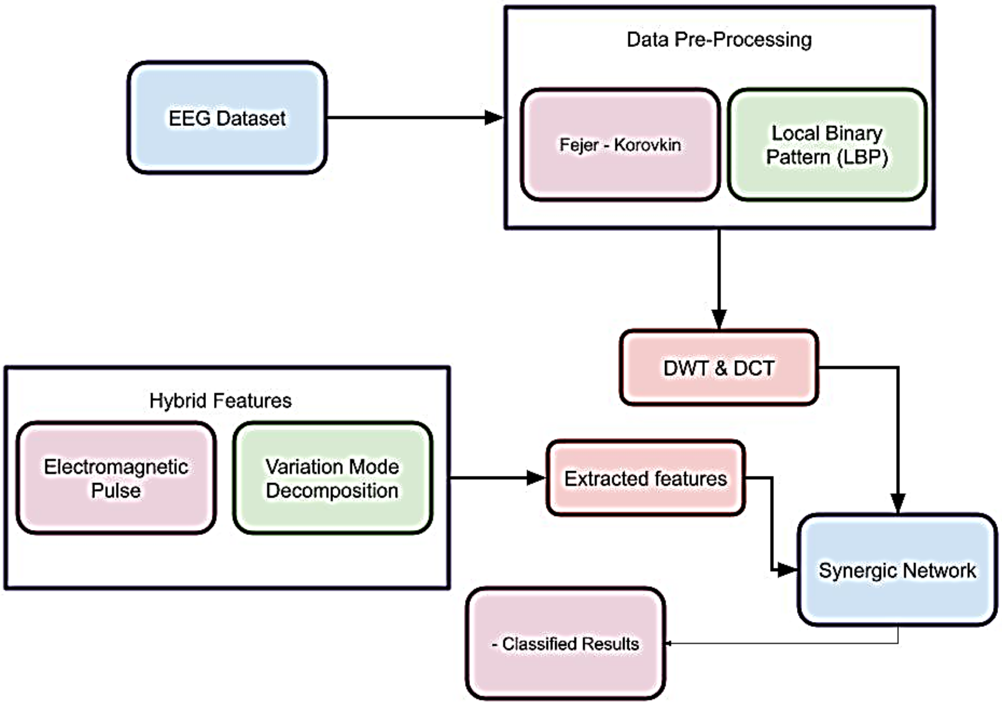

Figure 1. The overall process in SLBP.

The converted EEG signal in image format comprises the brightness and the non-uniform illumination parts that require the elimination of noises in the undesired regions with the extraction of the regions through the correction of shades and contrast enhancement. Considering the EEG signal, the variation in the signal is visible in bright colors for the green and blue channels. The high-intensity channel detects the artefacts in the signal for increased contrast. Low contrast is observed in the blue channel, and saturated channel is observed in the red channel. Additionally, the noisy and poor dynamic range information is computed and processed. The EEG structure comprises a dark pattern to improve the green channel's contrast. The developed SLBP model comprises elements with higher contrast for classifying the normal, moderate, and severe Schizophrenia signals. Figure 1 provides the steps in implementing the SLBP model for classifying Schizophrenia signals.

The SLBP estimates the variation in the signal frequencies with consideration of images in the background to increase the quality, contrast, and correction. With the SLBP model, the variation in the signal background is eliminated. The preprocessing is performed with the Fejer-Korovkin filter with the threshold values set as 30×30 to compute the spatial frequencies. The variation in the background of output is computed based on the green plane represented in equation (1)

$$\log(\theta) = -\frac{1}{M}\left[\sum x_{a=1}^{M} \sum y_{b=1}^{K} \sum y_{c=1}^{L} 1\{y^{(1)} = b\} \log \frac{e^{X_b^{(a)}}}{\sum_{l=1}^{K} z_1^{(a)}}\right] \quad (1)$$

The developed SLBP model comprises the synergic network with the data sequences of $\{x^{(1)}, x^{(2)}, \dots \cdots x^{(M)}\}$, with the resultant class value of $\{y^{(1)}, y^{(2)}, \dots . y^{(M)}\}$. The loss function in the sequences is computed based on the entropy values computed as in equation (2)

$$\log(\theta) = -\frac{1}{M}\left[\sum X_{a=1}^{M} \sum Y_{b=1}^{K} \sum y_{c=1}^{L} 1\{y^{(1)} = b\} \log \frac{e^{X_b^{(a)}}}{\sum z_1^{(a)}{}_{l=1}^{K}}\right] \quad (2)$$

The features utilized for the deep learning model is presented in equation (3) and (4)

$$\mathrm{f_A} = \mathcal{F}\left(\mathrm{Z_A}, \theta^{(\mathrm{a})}\right) \quad (3)$$

$$\mathrm{f_B} = \mathcal{F}\left(\mathrm{Z_B}, \theta^{(\mathrm{a})}\right) \quad (4)$$

$$\mathrm{f_c} = \mathcal{F}\left(\mathrm{Z_C}, \theta^{(\mathrm{a})}\right) \quad (5)$$

In the above equation (3), (4), and (5), the resultant class feature vector is denoted as $\mathrm{f_A}, \mathrm{f_B}$, and $\mathrm{f_c}$. θ is a parameter that the model tries to optimize during training. M represents the total number of data sequences in the training dataset. The machine learning model vector parameter is represented as $\theta^{(\mathrm{a})}$ with the normalized vector value of $\mathrm{Z_A Z_B}$ and $\mathrm{Z_C}$, and the functional parameter characteristics are stated as $\mathcal{F}$. The deep learning model performance with the SLBP is computed using the equation (6)

$$ys(Z_A, Z_B, Z_c) = \begin{cases} 1 & \text{if} \quad y_A \neq y_B = y_C \\ 0 & \text{if} \quad y_B \neq y_C \\ -1 & \quad Otherwise \end{cases}; \quad (6)$$

$\mathrm{f_A}, \mathrm{f_B}$, and $\mathrm{f_c}$ .are features obtained by applying a function F to the latent variables $\mathrm{Z_A}$, ZB, and $\mathrm{Z_c}$, respectively. $\theta^{(\mathrm{a})}$ represents the parameters of the function F for the corresponding feature. The $\mathrm{Z_A}, \mathrm{Z_B}$are latent variables related to the model's internal representations. The synergic deep learning model for the classification is computed with the sigmoidal layer with the estimation of the entropy features computed as in equation (7)

$$S|^{S}(\theta^{S}) = y_s \log \widehat{y_S} + (1 - y_s) \log(1 - \widehat{y_S}) \quad (7)$$

The training process with the consideration of 3-classes in the model of SLBP is presented in equation

$$\begin{cases} \theta^{(a)}(t+1) = \theta^{(a)}(t) - \eta(t) \cdot \Delta^{(a)} \\ \theta^{\mathrm{S}(a)}(t+1) = \theta^{\mathrm{S}(a)}(\mathrm{t}) - \eta(\mathrm{t}) \cdot \Delta^{\mathrm{S}(a,b)'} \\ \theta^{\mathrm{S}(a)}(t+1) = \theta^{\mathrm{S}(a)}(\mathrm{t}) - \eta(\mathrm{t}) \cdot \Delta^{\mathrm{S}(a,b,c)'} \end{cases} \quad (8)$$

$\vdash \mathrm{S} \dashv$ represents the true class label for a data sample S. It is one of the three classes in the 3-class classification problem. y_S is the predicted probability that the data sample S belongs to class $\vdash \mathrm{S} \dashv$, obtained from the model's output. $\theta^{S}$is a parameter vector associated with class $\vdash \mathrm{S} \dashv$. It includes the model's weights and biases related to class $\vdash \mathrm{S} \dashv$. log(y_S) is the natural logarithm of the predicted probability y. $(1 - y_s)$ is the complement of the predicted probability, representing the probability that the data sample S does not belong to class $\vdash \mathrm{S} \dashv$. $\log(1 - \widehat{y_S})$is the natural logarithm of (1 - y_S). With the developed SLBP learning rate of the model, a synergic network is performed using the equations (9) and (10)

$$\Delta^{(a)} = \frac{\partial l^{(a)}(\theta^{(a)})}{\partial \theta^{(a)}} + \lambda \sum_{b=1,\mathrm{c}\neq b\neq a}^{n} \frac{\partial I^{S(a)}(\theta^{S(a,b,c)})}{\partial \theta^{S(a,b,c)}} \tag{9}$$

$$\Delta^{\mathrm{S}(a)} = \frac{\partial \mathrm{I}^{\mathrm{S}(a)}(\theta^{\mathrm{S}(a,b,c)})}{\partial \theta^{\mathrm{S}(a,b,c)}} \tag{10}$$

The assigned data label for the proposed SLBP model is evaluated based on the consideration of equation (11)

$$y(Z) = \underset{j}{\operatorname{argmax}} \left\{ \sum_{i=1}^{k} p_1^{(i)}, \dots, \sum_{i=1}^{k} p_j^{(i)}, \dots, \sum_{j=1}^{k} p_K^{(i)} \right. \tag{11}$$

The Fejer- Korovkin filter reduces distortion without affecting the signal's edges. To prevent sharp edges, it reduces random noise to a minimum. With sliding windows, the neighboring pixel value estimation is done using the Fejer-Korovkin filter. The Fejer-Korovkin filter eliminates signals' salt and pepper noise and horizontal scanning artifacts because it can only filter outliers. Most of the time, contrast enhancement improves an object's appearance by increasing the brightness difference between the object and its background. The examined EEG signals lack contrast and contain photographic artifacts. To increase contrast, preprocessing methods are applied to the EEG signals. Histogram evening out is utilized at first, and it is observed that the result could be more sufficiently productive. The central portion of the signal and the ODregion are significantly enhanced because the histogram equalization technique treats the EEG signal globally. It may miss some lesions and does not respond well to local contrast enhancement.

3.1. Segmentation of EEG signal for earlier detection of Schizophrenia

Next to preprocessing, the segmentation is performed for the estimation of the morphological characteristics of the signal for the classification of the normal, moderate, and severe. The SLBP model evaluates the brightness level to remove OD to perform the morphological operation in the signals. The intensity level of the signal is computed with the estimation of lesions in the images to reduce the false detection rate. The classification accuracy is improved through the effective detection model by applying the morphological transformation methods. The morphological characteristics of the signal are estimated based on removing the signal pixel in the foreground. The output signal is effectively processed with the operation based on the consideration of input sequences to perform the mathematical operation as presented in equation (12)

$$X^{\circ}B = (X^{\circ}B)\oplus \mathrm{B} \tag{12}$$

The EEG signal closing operation are computed based on the equation (13)

$$X.B = (X\oplus \mathrm{B})\Theta \mathrm{B} \tag{13}$$

The green channel signal X images are estimated using the morphological structure B. The morphological operation in the gray scale is represented as $\oplus$, with the symbol represented as (●). The detecting rate is computed as in equation (14)

$$X = \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} XY = \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} Y = \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} YZ = \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} Z =$$

$$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} XZ = \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} E \tag{14}$$

The green channel is estimated based on the segmentation with the SLBP model computed using the equation (15) and (16)

$$E(C) = \mu^x \int_c g_b(\nabla\nabla I(C(s)))\big(d_x + \big(\int_{\text{Cin}} (I(x) - \text{Cin})^2\big)d_x + \int_{\text{Cout}} (I(x) - \text{Cout})^2 d_x \tag{15}$$

$$E(f) = \sum_{r\in\mathbb{R}} D_r(f_r) + \sum_{r,S\in N} V_{r,s}(f_r, f_r) \tag{16}$$

The segmented signal features in the images are evaluated based on the consideration of equation (17)

$$E = \mu \times E_b(r,s) + E_\times(r) = \mu \sum_{r\in S\in R\in N(s)} \omega_n * \big((1 - x_r) \times_s\big) + \times_r (1 - x_s) \div (1 + \beta \mid I(r) - I(s)) + (\textstyle\sum_r)\big(I(r) - C_y\big)^2 (1 - x_r) + \sum_r (I(r) - C_t)^2 x_r \tag{17}$$

The coordinates of the signal are computed using the equation (18) and (19)

$$C_y = (\textstyle\sum_r) I(r) \div (\sum_r)(1 - \times_r) \tag{18}$$

$$C_t = (\textstyle\sum_r) I(r) \times \times_r \div (\sum_r \times_r) \tag{19}$$

The SLBP model uses the synergic network with the estimated segmentation value of $\beta > 0$ with consideration of constraints presented in equations (20) and (21)

$$E = E_b(r,s) X E'_r(r,s) \tag{20}$$

$$E' = \sum \min\Big(\big(I(r) - C_y\big)^2 + (I(s) - C_t)^2 + ((I(r) - C_t)^2) + \big(I(r) - C_y\big)^2\Big) \tag{21}$$

The signal constraints in the EEG signal are denoted as in equation (22)

$$\varphi(r) = \big(I(r) - C_y\big)^2, \varphi(r) = (I(r) - C_t)^2, \Delta\varphi(p) = \big(\mid \varphi_y(r) - \varphi_t(p)\big)\big) \div 2 \tag{22}$$

The inequality constraints in the synergic network are presented in equation (23)

$$\varphi(r) > \varphi(r) + \Delta\varphi(p) \tag{23}$$

E(C) and E(f) represent energy functions, where C and f are certain signals or signal features. The equations involve integrals, gradients, and summations for computing the energy values based on given coefficients. The overall energy E combines several energy terms, each with different weights (ω_n). The equation involves summations and manipulations of signal features (x_r, x_s, I(r), C_y, C_t, etc.). The energy term E and an auxiliary term E^'. E is calculated as combining two energy

terms, E_b and E_r'' with certain coefficients. The signal constraints are denoted by φ(r) and Δφ(p).
Steps involved in SLBP

Step0 : Converting the signal data in to image formatting
Step1 : Perform the image preprocessing
Step2 : Fejer-Korovkin filter for enhancement of EEG signals
Step3 : Apply the thresholding estimation model with the Local entropy for the segmentation of background.
Step4 : Compute the texture features such as GLCM and LBP
Step5 : Estimate the morphological characteristics for the detection
Step6 : Statistical feature selection based on one-way ANOVA test
Step7 : Classification with synergic network as normal, mild, and severe Schizophren

3.2. Modified local entropy thresholding operation with SLBP

The segmentation process is improved using the preprocessed image obtained from the Fejer-Korovkin filter. The estimation is performed based on the thresholding methods. The thresholding operation is performed based on entropy estimation in the EEG signal with the estimation of the co-occurrence to estimate the entropy with the reduced peak. The local thresholding is performed for the local entropy values to improve the spatical relation between foreground and background. The local entropy values are estimated based on the extracted signal using the thresholding operation to increase the extraction accuracy.

3.3. Synergic network for feature extraction with SLBP

The next stage is the feature extraction in the segmented signal to estimate the features. The features considered are statistical, energy, contrast, entropy, contrast, correlation, homogeneity, standard deviation, mean, and new texture-based LBP features. One-way ANOVA is implemented to select the best features by considering those features. The SLBP model uses the DCT, DWT, EMP, and VMD characteristics to train and test the model for classifying schizophrenia normal, mild, and severe cases. Figure 2 provides the steps in the feature extraction process.

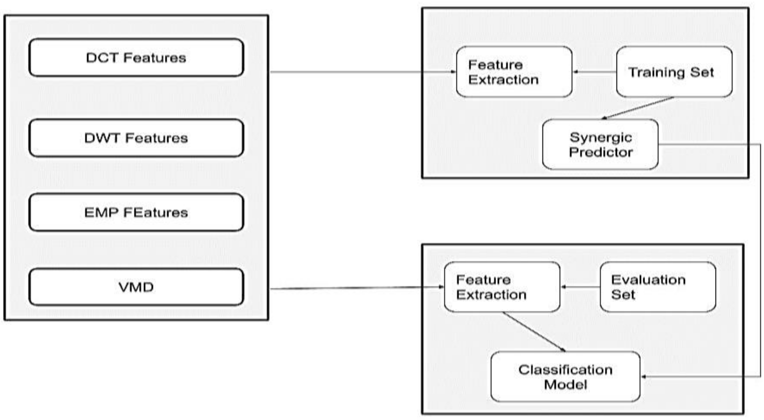

Figure 2. Feature extraction with SLBP.

The LBP feature vector is calculated by considering the neighborhood values based on the center pixel P with the overall radius of R. The radius of circle R is equal to the value of 1. The radius of the circle can range from 8 to 16 neighborhoods with the estimation of the texture descriptors in the histogram. Each pixel radiusm is computed with each bit stream marked as the 0 s and 1 s with the center pixel intensity or minimal neighbouring values to generate binary values. The LBP histogram is utilized for the estimation of the signal microstructure characteristics.

The SLBP model uses the LBP operator in the uniform pattern of circular transition represented in the range of 0 to 1. The texture descriptors are utilized ofr calculating uniform pixels microstructure pattern detection in the edges. Through the consideration of the patterns in the neighborhood, the transitions are computed based on the invariant operation calculated as LBPP,R. The pattern in LBP is evaluated based on the uniformity measures represented as U for the estimation of spatial pattern. The SLBP model uses the LBP feature for the extraction calculated based on the consideration of histogram and texture. The examination is based on considering a total of 9 LBP features in the EEG signal with the consideration of feature descriptors. The synergic network architecture is presented in Figure 3.

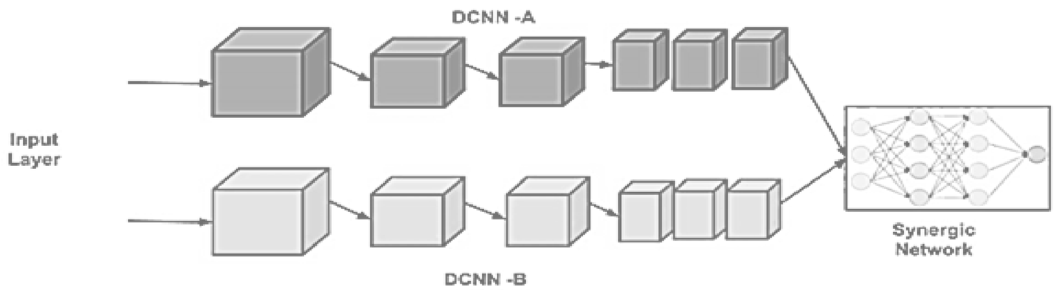

Figure 3. Process in a synergic network.

The synergic network classifies normal, mild, and severe cases. The SLBP model comprises the hidden neurons and activation function for the estimation from 25 to 65 with a total hidden neuron count of 45.

4. Results and discussion

The experimental simulation has been performed on Pythonwith3.2GHz-i5processor.

Dataset: The performance of the proposed SLBP model is evaluated for the dataset EEG Psychiatric Disorders Dataset and Schizophrenia data downloaded in the website link of https://www.kaggle.com/datasets/broach/button-tone-sz and https://www.kaggle.com/datasets/shashwatwork/eeg-psychiatric-disorders-dataset?select=EEG.machinelearing_data_BRMH.csv.

Button Tone SZ: This dataset contains EEG recordings collected during an auditory oddball task from individuals with schizophrenia. The auditory oddball task is a commonly used paradigm to study cognitive processes, including attention and working memory. Participants are presented with auditory stimuli in this task, typically high-frequency "target" and low-frequency "non-target" tones.

The Button Tone SZ dataset likely includes EEG signals recorded from electrodes placed on the scalps of individuals with schizophrenia while they performed the auditory oddball task. These EEG recordings capture the brain's electrical activity, precisely the neural responses related to auditory processing and cognitive functions. The dataset may include electrode placement, task performance labels, and other demographic or clinical information about the participants.

EEG Psychiatric Disorders Dataset: The EEG Psychiatric Disorders dataset collects EEG recordings from individuals with various psychiatric disorders. This dataset aims to provide valuable information on the brainwave patterns associated with different psychiatric conditions. It may include EEG data from individuals diagnosed with schizophrenia, depression, anxiety, or bipolar disorder. The dataset likely contains EEG signals recorded from participants in different mental states or performing specific tasks. It may also include additional information such as demographic details, diagnostic labels, or clinical scores related to the psychiatric disorders.

The collected dataset comprises the information about the 81 patients. The information about other disorders, such as depression, personality, anxiety, eating, and addiction, is also incorporated. The data related to healthy control groups are collected from the website https://repod.icm.edu.pl/dataset.xhtml?persistentId=doi:10.18150/repod.0107441. This dataset comprises patient information. The EEG signal estimated for the EMP-IMF is presented in Figure 4.

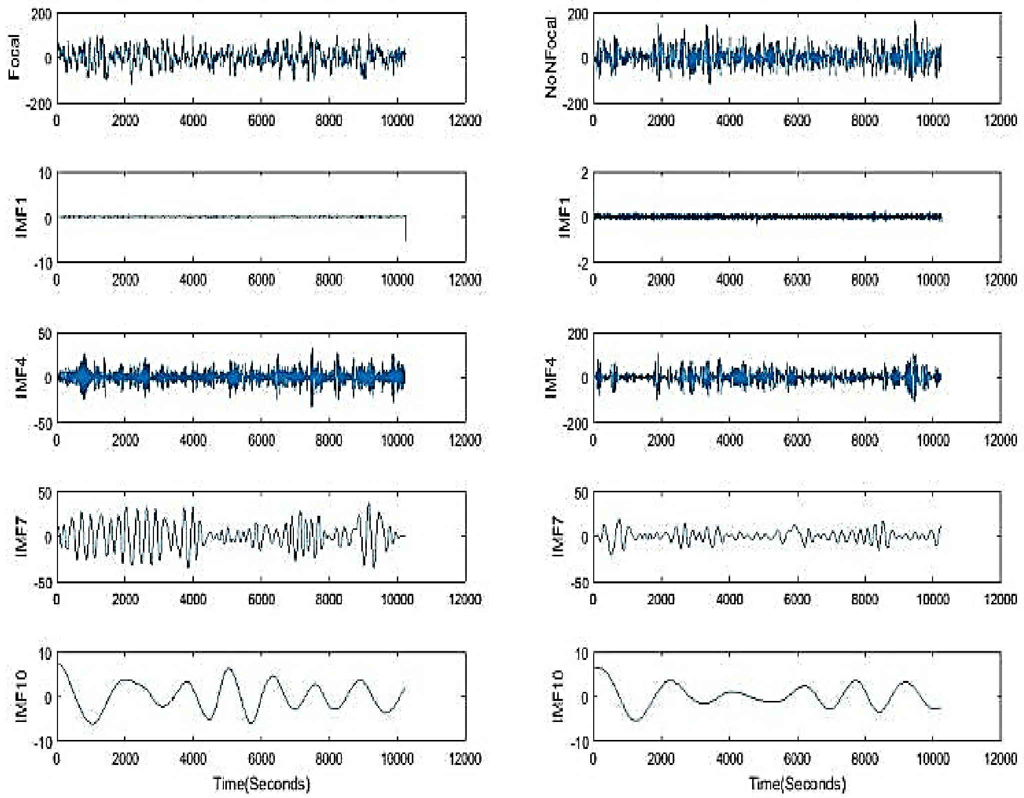

Figure 4. EMP–IMF process with SLBP.

The signal features are extracted considering the DWT and EMP, presented in Table 1.

Table 1. Estimation of entropy.

Signal1	Shannon Entropy	Log Energy Entropy	Renyi Entropy
DWT1	254.13	-28622.09	63.86
DWT2	-8070.96	-1737.45	79.07
DWT3	-247691.41	2907.28	85.42
DWT4	-1497379.52	2767.93	88.14
DWT5	-563368697.30	6327.12	112.52

Table 2. Entropy in DWT.

Signal1	Shannon Entropy	Energy Entropy	Renyi Entropy
DWT1	254.13	-28622.09	63.86
DWT2	-8070.96	-1737.45	79.07
DWT3	-247691.41	2907.28	85.42
DWT4	-1497379.52	2767.93	88.14
DWT5	-563368697.30	6327.12	112.52

Table 3. EMP Features in SLBP.

Signal1	Shannon Entropy	Log Energy Entropy	Renyi Entropy
EMP1	200.20	-67146.88	66.52
EMP2	1549.12	-30950.78	82.30
EMP3	-96134.70	-6745.75	93.35
EMP4	-1974360.93	9473.44	102.24
EMP5	-11356141.03	36872.95	112.71
EMP6	-20711461.61	41403.32	114.97
EMP7	-75137400.36	54540.13	120.31
EMP8	-188531825.40	65940.67	124.73
EMP9	-28140530.41	47315.68	116.85
EMP 10	-809574.14	18937.69	103.83
EMP 11	-181871.52	12610.84	100.05

The EEG signal sample focal and non-focal are estimated based on the DWT and EMP domains, as presented in Table 1-3. The entropy features for the focal and non-focal points are estimated based on the entropy features for the extraction and classification. The SLBP model classifications the signal into five sub-bands for the computation of the signal with sub-sets of S, F, N, O, and Z. The estimated entropy values are computed and presented in Table 1–3.

Table 4. Features of the signal.

Signal1	Differential Entropy (DE)	Peak Root Mean Square (PRMS)
VMD1	3.66	3.71
VMD2	2.23	3.79
VMD3	1.33	6.53
VMD4	1.10	7.10
VMD5	2.83	3.64
VMD6	3.26	4.26
VMD7	2.24	3.57
VMD8	1.93	6.68
VMD9	1.57	7.21
VMD10	0.81	9.99

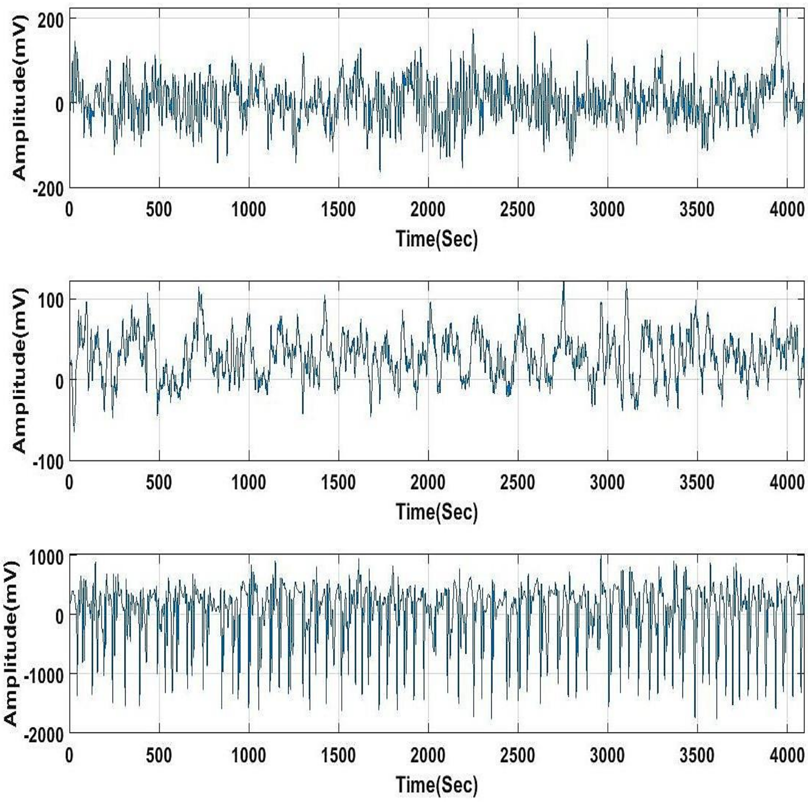

Figure 5. EEG signal characteristics.

The features of differential entropy and PRMS are extracted from the given data. SLBP classifier uses these features and builds the tree. The test data are classified as presented in Figure 5. EEG signal is classified for artifacts, and normal signal and accuracy of the classification are measured. Feature vectors of EEG signals for normal, mild, and severe signals have been extracted, and sample feature values are shown in Table 4.

The proposed SLBP is evaluated for the BB-EEG dataset to evaluate the performance of the proposed model with the existing methods. In Table 9, the performance of the SLBP is validated for the different parameter's sensitivity, specificity, PPV, and NPV values. The performance of the proposed SLBp model is validated with the EEG signal value of 80% for training and testing data comprised of 20%. The performance of the proposed SLBP model achieves an accuracy of 98% while existing models NB, KNN, NN, and SVM provide 80%, 90%, 90%, and 90% of sensitivity, respectively, as presented in Table 5.

Table 5. Performance analysis.

EEG Dataset									
Database	Classifiers	TP	FP	FN	TN	Sensitivity(%)	Specificity(%)	PPV(%)	NPV(%)
Normal	NavieBayes	10	2	1	18	92.98	93.73	91.67	92.36
	K-NN	10	3	1	17	92.57	84.24	72.15	93.14
	NN	10	1	1	19	92.35	92.73	93.783	93.92
	SVM	10	1	0	21	92.24	93.25	93.91	94.82
	SLBP	9	0	1	20	100	96.36	98.25	98.62
Mild	NavieBayes	10	3	1	17	93.51	83.24	73.71	9.15
	K-NN	8	3	2	18	75.72	83.24	72.64	85.71
	NN	9	10	0	10	95.34	48.27	49.91	92.82
	SVM	9	4	1	16	95.34	83.18	79.68	93.93
	SLBP	9	1	1	12	99.24	98.81	99.47	99.84
Severe	NavieBayes	9	0	2	10	85.61	100	100	91.94
	K-NN	8	1	2	13	76.21	100	100	88.95
	NN	1	1	9	16	10.24	100	0	66.74
	SVM	6	0	1	18	75.24	100	100	93.83
	SLBP	4	1	3	21	96.82	100	100	98.74

Table 6. Comparison of accuracy.

Dataset	Classifiers	Accuracy (%)
EEG Database	Naive bayes	68.35
	SVM	76.74
	NN	72.05
	NB	78.96
	SLBP	98.57
EEG database	Naive bayes	90.95
	K-NN	77.86
	NN	60.07
	SVM	91.82
	SLBP	98.63

Similarly, the proposed SLBP model achieves a % PPV value of 96% while existing methods NB, KNN, NNandSVMdeliver88.33%, 79.74%, 49.20%, and 92.30%. Additionally, the proposed SLBP model NPV model achieves an accuracy of 98% with the existing model NPV value of NB, KNN, NN, and SVM deliver 93.45%, 88.69%, 87.30%, and 95.38%, as presented in Table 6.

The SLBP cross-validation results are shown in Table 7. The chosen datasets undergo this cross-validation procedure. The sensitivity of the RF method is 95%, the specificity is 95%, and the accuracy for the database is 78.5%, 94.1%. PPV and NPV of seizure classification are 95.45%, 93.63%, 95.45%, and 96.74% for both BB-EEG and BU-EEG databases, respectively. The EEG signals' mutual information is normal: 2.44, mild: 1.74, and severe: 2.6, respectively.

Table 7. Cross-validation of proposed methodology.

Parameters	Dataset	BU-EEG database
Feature	DE and PRMS	DE and PRMS
Classification	RF	RF
Total Samples	7300	600
Training	70	150
Testing	30	40
True Positive (TP)	91	112
False Positive (FP)	14	30
True Negative (TN)	90	280
False Negative (FN)	15	30
Accuracy(%)	98.34	98.72
Sensitivity(%)	97.82	97.94
Specificity(%)	97.82	97.93
Positive Prediction Value (PPV) (%)	96.73	96.82
Negative Prediction Value (NPV) (%)	96.63	96.94
Mutual information	Normal: 1.2780 Abnormal: 1.478	Normal: 2.44 Mild: 2.6 Severe: 1.74

The performance of EEG data with the SLBP model is compared with the existing classifiers such as DNN, RF, and SVM classifiers. In Table 8, the comparative analysis expressed that the proposed SLBP model exhibits higher sensitivity and specificity. The performance is evaluated based on the consideration of random EEG signal samples. The simulation analysis expressed that the proposed SLBP model exhibits a higher accuracy value of 98% than the existing methodology. SVM, CNN, and RF deliver 65.25%, 78.905%, and 89.015% of sensitivity. Correspondingly, the average specificity of the proposed system is 93.89%, and the existing techniques deliver 48.335%, 64.585%, and 69.79% of specificity.

In Table 8, the BU-EEG database is used for associating the performance evaluation of the proposed and the existing methodologies. The BU-EEG database considers three classes for disease classification: asictal, interictal, and normal. In this scenario, the performance evaluation is validated for random sample EEG signals with 70% of training and 30% of testing. The average sensitivity of the proposed method delivers 95.833%, and the existing approaches delivers 74.10%, 78.57%, and 87.01% of sensitivity. In addition, the average specificity of the proposed method is 95.65%, and the existing techniques deliver 61.01%,76.78%, and 88.93% of specificity. The performance evaluation of the EEG database is presented in Table 8 and Table 9.

Table 8. Comparison of EEG Dat set.

EEG Data							
Classes	Classifiers	TP	FP	FN	TN	Sensitivity (%)	Specificity (%)
	SVM	11	7	5	7	68.75	50.63
	CNN	12	5	4	9	75.86	64.28
Normal	RF	13	2	3	12	81.25	85.71
	SLBP	15	1	1	13	93.75	92.85
Interictal	SVM	12	5	4	9	75.86	64.28
	CNN	12	3	4	11	75.95	78.57
	RF	14	1	2	13	87.50	92.85
	SLBP	15	0	1	14	93.75	100
Ictal	SVM	11	5	3	11	78.57	68.75
	CNN	12	2	2	14	85.71	87.50
	RF	12	2	1	15	92.30	88.23
	SLBP	13	1	0	16	100	96.94

Table 9. Performance evaluation.

EEG Data							
Classes	Classifiers	TP	FP	FN	TN	F-score(%)	MCC(%)
Normal	SVM	11	7	5	7	64.70	19.09
	CNN	12	5	4	9	72.72	39.55
	RF	13	2	3	12	83.87	66.81
	SLBP	15	1	1	13	93.75	96.60
Mild	SVM	12	5	4	9	72.72	39.55
	CNN	12	3	4	11	77.41	53.45
	RF	14	1	2	13	90.32	80.17
	SLBP	15	0	1	14	96.77	93.54
Severe	SVM	11	5	3	11	73.33	47.32
	CNN	12	2	2	14	85.71	73.21
	RF	12	2	1	15	88.88	80.84
	SLBP	13	1	0	16	96.29	93.48

In Table 9, the proposed SLBP model computes the Schizophrenia detection with an improved performance ~12% higher than the classification accuracy for the EEG dataset and BU-EEG database. The accuracy estimation of the proposed SLBP model is presented in Table 10.

Table 10. Comparison of accuracy.

Dataset	Classifiers	Feature extraction method	Preprocessing method	Accuracy(%)
Normal	SVM [16]	WPE (Wavelet Packet Entropy), KICA (Kernel Independent Component Analysis)	CSP filter and wavelet threshold denoising	58.99
	CNN [21]	WPE,KICA	CSPfilterandwaveletthresholddenoising	65.42
	RF [22]	WPE,KICA	CSPfilterandwaveletthresholddenoising	81.34
	SLBP	WPE,KICA	Fejer-Korovkinandwaveletthresholddenoising	92.56
Mild and Severe	SVM	WPE,KICA	CSPfilterandwaveletthresholddenoising	66.84
	CNN	WPE,KICA	CSPfilterandwaveletthresholddenoising	74.08
	RF	WPE,KICA	CSPfilterandwaveletthresholddenoising	83.52
	SLBP	WPE,KICA	Fejer-Korovkinandwaveletthresholddenoising	98.38

Table 11. Overall comparative analysis.

References	Database	Features considered	Classification method	Accuracy (%)
[19]	BU-EEG database	Permutation entropy	SVM	84.17
[20]	BU-EEG database	DTCWT	ANN and SVM	83.53
SLBP	EEG database	WPE,KICA	SLBP	98.93
SLBP	BU-EEG database	WPE,KICA	SLBP	98.84

The comparative study is shown in Table 11. The comparative analysis of the proposed SLBP model with the existing [19] and [20] provides a higher % classification accuracy of 98%. Through the LBP model, the synergic network estimates the signal features and classifies the signal effectively compared with the existing techniques. The proposed SLBP model's advantages are as follows: The proposed SLBP model achieves a classification accuracy of 98%, approximately 12% higher than existing methods. This higher accuracy can lead to more reliable and accurate diagnoses of schizophrenia severity, enabling appropriate medical interventions. The SLBP model utilizes statistical features for the computation of EEG signal characteristics. By extracting relevant features from the EEG signals, the model can capture the distinctive patterns associated with schizophrenia. This efficient feature extraction contributes to improved classification accuracy. As the size of EEG databases continues to increase, there is a need for methods that can handle large amounts of data. The proposed method addresses this challenge by providing a solution for processing and analyzing large EEG databases. This capability allows for faster diagnosis and handling of vast information. The research considers three classes: normal, mild schizophrenia, and severe schizophrenia. By classifying EEG signals into these categories, the method allows for the earlier prediction of schizophrenia stages. This can be valuable for healthcare professionals in providing appropriate treatment plans and interventions. Developing an automatic schizophrenia detection method reduces the reliance on manual operations and subjective assessments by neurophysicians. This automation can save time and effort in the diagnosis process, enabling faster and more efficient medical decision-making. The research contributes to clinical neuroscience by providing an efficient and accurate diagnosis of schizophrenia severity based on EEG signals. The proposed model has the potential to be applied in real-world clinical settings, assisting healthcare professionals in diagnosing and treating schizophrenia patients. The research limitations are presented as follows: The research may have focused on specific EEG-based brain-computer interface spellers or experimental conditions, which could limit the generalizability of the findings to other systems or scenarios. The effectiveness of the proposed friend-guard adversarial noise approach may need to be evaluated across different EEG-based systems and settings. The research might have relied on simulated or controlled experimental data, which may not fully capture the complexity and variability of real-world EEG signals. The performance and robustness of the proposed method in real-world scenarios need to be further investigated. The research might have considered a specific set of adversarial attack scenarios, neglecting other potential attacks relevant to EEG-based systems. The investigation of a broader range of attack scenarios would provide a more comprehensive assessment of the method's effectiveness. The proposed method may incur additional computational complexity or resource requirements due to the injection and processing of adversarial noise. The impact of this computational overhead on the system's real-time performance and practical implementation needs to be considered. The research may have yet to thoroughly explore the potential impact of the friend-guard adversarial noise on the user experience, user acceptance, and usability of EEG-based systems. The acceptance and usability of the proposed approach by end-users should be considered to ensure its practical viability.

5. Conclusions

The prediction of EEG signal-based techniques is a significant area of research in computer-aided health monitoring systems. These methods involve extracting features, such as differential entropy and PMRS, from input EEG data while eliminating irrelevant features using the proposed Statistical Local Binary Pattern (SLBP). These statistical features are computed to characterize the EEG signals. The proposed SLBP model incorporates a Local Binary Pattern to analyze the texture of the labeled signal, estimating the neighborhood through a binary search operation. Classification is performed to predict the schizophrenia stage, either mild or severe, considering three classes: normal, mild, and severe. This paper constructed and presented the extraction of features using SLBP in EEG signals to improve classification performance. The proposed method is compared with existing methods, and the results demonstrate a higher classification accuracy ranging from 4 to 10% compared to those existing methods. This suggests that the inclusion of multiple features, as opposed to using them individually, enhances the performance of the classification task. It is concluded that using SLBP and multiple features improves the accuracy of classifying EEG signals in predicting the severity of schizophrenia. This research contributes to developing more effective techniques for EEG-based prediction and diagnosis in the context of mental disorders.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflict of interest.

Author contributions

All authors have contributed equally to the conception of the work, drafting the paper, approving the final version to be published, and answering the reviewer's queries and have taken care of the accuracy and integrity of the work.

Reference

1. Pahuja SK, Veer K (2022) Recent approaches on classification and feature extraction of EEG signal: a review. *Robotica* 40: 77–101. https://doi.org/10.1017/S0263574721000382
2. Wang J, Wang M (2021) Review of the emotional feature extraction and classification using EEG signals. *Cogn Robot* 1: 29–40. https://doi.org/10.1016/j.cogr.2021.04.001
3. Li MA, Han JF, Yang JF (2021) Automatic feature extraction and fusion recognition of motor imagery EEG using multilevel multiscale CNN. *Med Biol Eng Comput* 59: 2037–2050. https://doi.org/10.1007/s11517-021-02396-w
4. Baygin M, Dogan S, Tuncer T, et al. (2021) Automated ASD detection using hybrid deep lightweight features extracted from EEG signals. *Comput Biol Med* 134: 104548. https://doi.org/10.1016/j.compbiomed.2021.104548
5. Zheng X, Liu X, Zhang Y, et al. (2021) A portable HCI system-oriented EEG feature extraction and channel selection for emotion recognition. *Int J Intell Syst* 36: 152–176. https://doi.org/10.1002/int.22295
6. Tuncer T, Dogan S, Subasi A (2022) LEDPatNet19: Automated emotion recognition model based on nonlinear LED pattern feature extraction function using EEG signals. *Cogn Neurodynamics* 16: 779–790. https://doi.org/10.1007/s11571-021-09748-0
7. Suzuki K, Laohakangvalvit T, Matsubara R, et al. (2021) Constructing an emotion estimation model based on EEG/HRV indexes using feature extraction and feature selection algorithms. *Sensors* 21: 2910. https://doi.org/10.3390/s21092910
8. Tuncer T, Dogan S, Subasi A (2021) EEG-based driving fatigue detection using multilevel feature extraction and iterative hybrid feature selection. *Biomed Signal Proces* 68: 102591. https://doi.org/10.1016/j.bspc.2021.102591
9. Woodbright M, Verma B, Haidar A (2021) Autonomous deep feature extraction based method for epileptic EEG brain seizure classification. *Neurocomputing* 444: 30–37. https://doi.org/10.1016/j.neucom.2021.02.052

10. Ein Shoka AA, Alkinani MH, El-Sherbeny AS, et al. (2021) Automated seizure diagnosis system based on feature extraction and channel selection using EEG signals. *Brain Inform* 8: 1–16. https://doi.org/10.1186%2Fs40708-021-00123-7
11. Albaqami H, Hassan GM, Subasi A, et al. (2021) Automatic detection of abnormal EEG signals using wavelet feature extraction and gradient boosting decision tree. *Biomed Signal Proces* 70: 102957. https://doi.org/10.1016/j.bspc.2021.102957
12. Grossi E, Valbusa G, Buscema M (2021) Detection of an autism EEG signature from only two EEG channels through features extraction and advanced machine learning analysis. *Clin EEG Neurosci* 52: 330–337. https://doi.org/10.1177/1550059420982424
13. Deng X, Zhu J, Yang S (202) SFE-Net: EEG-based emotion recognition with symmetrical spatial feature extraction. *In Proceedings of the 29th ACM International Conference on Multimedia*, 2391–2400. https://doi.org/10.48550/arXiv.2104.06308
14. Kumar TR, Mahalaxmi U, Ramakrishna MM, et al. (2023) Optimization enabled deep residual neural network for motor signalry EEG signal classification. *Biomed Signal Proces* 80: 104317. https://doi.org/10.1016/j.bspc.2022.104317
15. de Paula PO, da Silva Costa TB, de Faissol Attux RR, et al. (2023) Classification of signal encoded SSVEP-based EEG signals using convolutional neural networks. *Expert Syst Appl* 214: 119096. https://doi.org/10.1016/j.eswa.2022.119096
16. Fei SW, Chu YB (2022) A novel classification strategy of motor signalry EEG signals utilizing WT-PSR-SVD-based MTSVM. *Expert Syst Appl* 199: 116901. https://doi.org/10.1016/j.artmed.2019.101787
17. Al-Salman W, Li Y, Oudah AY, et al. (2022) Sleep stage classification in EEG signals using the clustering approach based probability distribution features coupled with classification algorithms. *Neurosci Res* 188: 51–67. https://doi.org/10.1016/j.neures.2022.09.009
18. Ma W, Xue H, Sun X, et al. (2022) A novel multi-branch hybrid neural network for motor signalry EEG signal classification. *Biomed Signal Proces* 77: 103718. https://doi.org/10.1016/j.bspc.2022.103718
19. Abenna S, Nahid M, Bouyghf H, et al. (2022) EEG-based BCI: A novel improvement for EEG signals classification based on real-time preprocessing. *Comput Biol Med* 148: 105931. https://doi.org/10.1016/j.compbiomed.2022.105931
20. GS SK, Sampathila N, Tanmay T (2022) Wavelet based machine learning models for classification of human emotions using EEG signal. *Meas: Sens* 24: 100554. https://doi.org/10.1016/j.measen.2022.100554
21. Wang H, Yu H, Wang H (2022) EEG_GENet: A feature-level graph embedding method for motor signalry classification based on EEG signals. *Biocybern Biomed Eng* 42: 1023–1040. https://doi.org/10.1016/j.bbe.2022.08.003
22. Xiao P, Ma K, Gu L, et al. (2023) Inter-subject prediction of pediatric emergence delirium using feature selection and classification from spontaneous EEG signals. *Biomed Signal Proces* 80: 104359. https://doi.org/10.1016/j.bspc.2022.104359
23. Khare SK, Bajaj V, Acharya UR (2023) SchizoNET: a robust and accurate Margenau–Hill time-frequency distribution based deep neural network model for schizophrenia detection using EEG signals. *Physiol Meas* 44: 035005. http://dx.doi.org/10.1088/1361-6579/acbc06

24. Khare SK, March S, Barua PD, et al. (2023) Application of data fusion for automated detection of children with developmental and mental disorders: A systematic review of the last decade. *Inform Fusion* 99: 101898. https://doi.org/10.1016/j.inffus.2023.101898
25. Khare SK, Bajaj V (2022) A hybrid decision support system for automatic detection of Schizophrenia using EEG signals. *Comput Biol Med* 141: 105028. https://doi.org/10.1016/j.compbiomed.2021.105028
26. Khare SK, Bajaj V (2021) A self-learned decomposition and classification model for schizophrenia diagnosis. *Comput Meth Prog Bio* 211: 106450. https://doi.org/10.1016/j.cmpb.2021.106450
27. Siuly S, Khare SK, Bajaj V, et al. (2020) A computerized method for automatic detection of schizophrenia using EEG signals. *IEEE T Neur Sys Reh* 28: 2390–2400. https://doi.org/10.1109/TNSRE.2020.3022715
28. Khare SK, Bajaj V, Acharya UR (2021) SPWVD-CNN for automated detection of schizophrenia patients using EEG signals. *IEEE T Instrum Meas* 70: 1–9. https://doi.org/10.1109/TIM.2021.3070608 .
29. Khare SK, Bajaj V, Siuly S, et al. (2020) Classification of schizophrenia patients through empirical wavelet transformation using electroencephalogram signals, *Modelling and Analysis of Active Biopotential Signals in Healthcare*, Bristol: IOP Publishing, 1–1 to 1–26. https://doi.org/10.1088/978-0-7503-3279-8ch1.
30. Krishnan PT, Raj ANJ, Balasubramanian P, et al. (2020) Schizophrenia detection using multivariate empirical mode decomposition and entropy measures from multichannel EEG signal. *Biocybern Biomed Eng* 40: 1124–1139. https://doi.org/10.1016/j.bbe.2020.05.008
31. Aydemir E, Dogan S, Baygin M, et al. (2022) CGP17Pat: Automated schizophrenia detection based on a cyclic group of prime order patterns using EEG signals. *Healthcare* 10: 643. https://doi.org/10.3390/healthcare10040643.
32. Baygin M, Yaman O, Tuncer T, et al. (2021) Automated accurate schizophrenia detection system using Collatz pattern technique with EEG signals. *Biomed Signal Proces* 70: 102936. https://doi.org/10.1016/j.bspc.2021.102936.
33. Khare SK, Acharya UR (2023) An explainable and interpretable model for attention deficit hyperactivity disorder in children using EEG signals. *Comput Biol Med* 155: 106676. https://doi.org/10.1016/j.compbiomed.2023.106676.
34. Khare SK, Bajaj V, Sinha GR (2020) Automatic drowsiness detection based on variational nonlinear chirp mode decomposition using electroencephalogram signals, *Modelling and Analysis of Active Biopotential Signals in Healthcare*, Bristol: IOP Publishing, 5–1 to 5–25. https://doi.org/10.1088/978-0-7503-3279-8ch5