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Application of local configuration pattern for automated detection of schizophrenia with electroencephalogram signals

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Abstract

Recently, a mix of traditional and modern approaches have been proposed to detect brain abnormalities using bio-signal/bio-image-assisted methods. In hospitals, most of the initial/scheduled assessments consider the bio-signal-based appraisal, due to its non-invasive nature and low cost. Further, brain bio-signal scans can be recorded using a single/multi-channel electrode setup, which is further evaluated by an experienced doctor, as well as computer software, to identify the nature and severity of abnormality. In this paper, we describe the development of a system for computer supported detection (CSD) of schizophrenia using the electroencephalogram (EEG) signal collected with a 19-channel electrode array. Schizophrenia is a mental illness that interferes with the way an individual thinks and behaves. It is characterised by psychotic symptoms such as hallucinations or delusions, negative symptoms such as decreased motivation or a lack of interest in daily activities and cognitive symptoms such challenges in processing information to make informed decisions or staying focused. This research has utilized 1142 EEGs (516 normal and 626 schizophrenia) with a frame length of 25 s (6250 samples) for investigation. The work initially converts the EEG signals to images using a spectrogram. Local configuration pattern features were extracted from the images thereafter, and 10-fold validation technique was used wherein Student's t-test and z-score standardization were computed per fold. The highest accuracy of 97.20% was achieved with the K-nearest neighbour (KNN) classifier. The results obtained confirm that the KNN classifier is helpful in the rapid detection of schizophrenia. This work is one of the first studies to extract local configuration pattern features from spectrogram images, yielding a high accuracy of 97.20%, with reduced computational complexity.

KEYWORDS

EEG signal, K-nearest neighbour classifier, local configuration pattern, schizophrenia, spectrograms, student's t-test, 10-fold validation

1 | INTRODUCTION

Recently, several semi-automated/automated disease examination procedures have been proposed and implemented by investigators to diagnose a class of brain-related disorders (BRD) (Acharya et al., 2012; Gudigar, Raghavendra, Ciaccio, et al., 2019; Gudigar, Raghavendra, San, et al., 2019; Raja et al., 2018; Rajinikanth et al., 2017; Subudhi et al., 2018; Talo et al., 2019). The accessibility of recent therapeutic service has also helped in the recognition of a variety of brain disorders in the early phase, and it has also been found to be useful in suggesting probable handling actions to regulate and treat the disease (Acharya et al., 2019; Acharya, Oh, Hagiwara, Tan, & Adeli, 2018; Acharya, Oh, Hagiwara, Tan, Adeli, & Subha, 2018; Michielli et al., 2019; Oh et al., 2018; Sharma, Achuth, et al., 2018; Sharma, Deb, & Acharya, 2018; Yuvaraj et al., 2018). Schizophrenia is one of the BRD in humans which causes hallucinations and delusions in affected people (Picchioni & Murray, 2007), and early diagnosis may help them to recover from the disease impact. This effect also includes deformation in thinking, sensitivity, emotion, speech, sagacity of self, and activities. The abovementioned characteristics could be present due to the increased levels of dopamine neurotransmitters in the brain of a schizophrenic patient as compared with that of a normal individual. The 2019 report of the World Health Organization (WHO) revealed that schizophrenia is a chronic BRD affecting 20 million people globally every year (Schizophrenia, World Health Organisation, 2022). This disease causes substantial disability, and increases the premature death rate by 2–3 times as compared with unaffected persons (GBD 2017 Disease and Injury Incidence and Prevalence Collaborators, 2018). If the disease is recognized in its early phase, it may be managed with scheduled medication and psychosocial support. The WHO report also confirmed that most schizophrenia sufferers living in low- and middle-income countries will not have sufficient provision for disease diagnosis so that a treatment planning process could proceed (Laursen et al., 2014). Furthermore, 69% of persons known to be affected by schizophrenia do not receive suitable care (Lora et al., 2012).

Recently, a considerable number of recognition and treatment planning procedures have been proposed to treat patients at the hospital level, as well as in home care with the supervision of family members. Different studies performed in past years have confirmed that the diagnosis of schizophrenia can be carried out with bio-signal-based procedures, which include the collection of (EEGs) obtained by using a suitable electrode array. EEG signals form due to events occurring in neurons within the brain and are usually documented with single/multi-channel electrodes placed on the scalp area. EEG signals are also efficient in providing information on other BRDs, such as dementia, Alzheimer's disease (AD), sleep disorder, and epilepsy (Bhattacharyya et al., 2017; Bhattacharyya et al., 2018; Gupta et al., 2017; Sharma et al., 2017; Sharma, Deb, & Acharya, 2018; Tripathy & Acharya, 2018; Yıldırım et al., 2018).

Our research aims to construct a computer supported detection (CSD) system to detect schizophrenia by evaluating the signal patterns of multi-channel EEG signals. The clinical level detection of schizophrenia is according to the history of complaint and the occurrence of neurological and psychological features (Jahmunah et al., 2019). The medical and/or activities of the patient may be gathered from family and friends before the decision is executed. Essential information regarding the patient, such as gender, diet, use of drug/medicines, and behaviour, are also considered during schizophrenia diagnosis.

Different CSD systems have been developed and executed by investigators to examine the incidence and degree of schizophrenia (Dvey-Aharon et al., 2015). Our present work also aims to develop a novel CSD system to recognize the disease with greater accuracy. The work consists of the following phases: (i) Conversion of 1-dimensional (1D) signals (19 channel) EEG with surface electrodes to 2-dimensional (2D) images, (ii) Extraction of image features from the images, (iii) Selection of significant features, (iv) Training and testing of classifiers and (v) validation and performance confirmation. This work was executed using EEG tracings, supported in examination of schizophrenia using the clinical-grade EEG signal database provided by Olejarczyk and Jernajczyk (2017), EEG Database et al. (2017). In this database, the number of signal samples/volunteers is large, and hence a segmentation technique was implemented to extract a signal sequence, with 6250 samples. The segmented EEG signal was then evaluated with our proposed CSD system. Our system confirmed that the detection accuracy of CSD improves with the K-nearest neighbour (KNN) classifier (97.20%) as compared to other classifiers considered in this research work. The outcome of this study also confirmed that the discussed technique is easy to implement, and can be employed to detect schizophrenia from EEG tracings collected from patients. This work is one of the first studies to extract local configuration pattern features from the spectrogram images, obtaining a high accuracy of 97.20% with reduced computational complexity. This paper is structured as follows: Section 1 provides the background of schizophrenia, Section 2 provides the context for developing a CSD system, Section 3 describes the main aim of research, Section 4 discusses the proposed methodology, Section 5 discusses the results and compares the current study with related studies and Section 6 concludes the work.

2 | CONTEXT

Due to its clinical significance, many EEG guided brain abnormality assessment techniques have previously been proposed and implemented to evaluate various illnesses. Schizophrenia is one such abnormality (Khare et al., 2021; Sharma & Acharya, 2021); it affects a considerable number of persons globally, and early detection and hospital/home supported care should reduce disease impact. Multi-channel EEG is a proven diagnostic procedure in which the required EEG signals are collected from patients using a non-invasive scalp electrode array, and these signals are then assessed with conventional/recent evaluation procedures. Normally, the conventional approach requires the assistance of an experienced doctor, who will examine the signal pattern physically to recognize the nature and degree of abnormality. This is a time-consuming process and hence, CSD systems have been proposed to assist the doctor in assessing EEG signals (Lai et al., 2021). The recent (past 6 years) schizophrenia assessment methods using traditional machine learning methods with EEG signals and images are summarized in Tables 1 and 2, respectively. From the table, it is observable that most authors had explored common techniques such as non-linear feature extraction, statistical feature extraction and wavelet transform methods. While some authors had explored different methods ranging from feature extraction methods using optimization techniques to spectral analysis of frequency bands and multivariate patterns analysis, these studies were all conducted using EEG signals. The current study is one of the earliest to have uniquely extracted local configuration patterns on spectrogram images for the classification of schizophrenia with EEG signals.

3 | PROBLEM FORMULATION

This research aims to execute a clinically significant CSD system to detect schizophrenia using multi-channel EEG obtained with a suitable electrode array. Recording and examining the EEG is a difficult task due to its multi-level signature. Moreover, the complexity of the assessment will increase based on the span of the EEG to be assessed. Hence, in this work, a segmentation procedure is implemented to limit the span of the EEG to the appropriate level, and the signal is converted into imagery prior to assessment. This work considered 28 volunteers' EEGs (14 normal and 14 disease classes) and the collected EEG was then segmented into 6250 samples. Then these samples were analysed using our proposed CSD to detect the schizophrenia class of EEG with enhanced accuracy.

4 | METHODOLOGY

The proposed research work aims to execute a CSD to diagnose the segmented EEG signal with superior accuracy. The scheme executed in this CSD can be found in Figure 2. Initially, a clinical trial is initiated to acquire a 19-channel EEG sequence from volunteers ($N = 28$), and the acquired EEG are then segmented into 6250 samples (25 s sequences) with repeated patterns. The density of this EEG is large, and assessment of these patterns for all 19 channels is complex and time-consuming. Hence, the existing 1-dimensional EEG signals are converted to 2-dimensional images using the short-time Fourier transform (STFT). Local configuration pattern (LCP) features are extracted from the grey images thereafter. Highly significant features are selected with Student's *t*- test. This feature set is then input to an array of classifiers, for the classification task. Figure 1 shows the various stages involved in the development of our automated system.

4.1 | Database preparation and pre-processing

Collection of clinical-grade schizophrenia EEG signals requires a complex preparation process and also the co-operation of volunteers who suffer from the disease. This work considered the multi-channel EEG database recorded and used by Olejarczyk and Jernajczyk (Olejarczyk & Jernajczyk, 2017), and this data set consists of 28 high-quality EEG sequences, which can be accessed from (EEG Database et al., 2017). The segmented signals were rescaled and normalised in the range 0 to 1. Table 3 presents information about the EEG signals. The actual EEG of normal/schizophrenia class of samples are complex to view and evaluate. Furthermore, the patterns of EEG are repetitive when it is recorded in a controlled environment. Hence, to minimize complexity, repeating patterns were segmented, and a new data set was constructed with 6250 samples/sequences. This segmentation procedure provided 1142 values from EEG sequences, which were then evaluated with the proposed CSD. Figure 2 depicts a sample EEG sequence, in which Figure 2a presents the disease class EEG, and Figure 2b depicts that of the normal class. These EEGs were acquired using a sampling frequency of 250 Hz with a 10–20 EEG montage and standard electrode locations: Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2. Other information about the signals can be found in (EEG Database et al., 2017).

4.2 | Conversion to spectrogram images

The pre-processed signals were then transformed into 2-D time-frequency spectrograms using the short-time Fourier transform (Huang et al., 2019). EEG signals are non-stationary, wherein the spontaneous frequency changes according to time. Thus, the characteristics of the changes cannot be explained using information from the frequency domain alone. Hence, the STFT, which is derived from the discrete Fourier Transform, is used to analyse the time-frequency characteristics (Huang et al., 2019). The spectrograms were obtained using a window of 10 samples with 0 overlap along the y-axis. The obtained STFT coefficients were separated into magnitude and angle components, where each column

TABLE 1 A summary of studies using machine learning methods with EEG signals for classification

Reference	Database	Methodology: Non-linear feature extraction	Model/classifier used	Accuracy (%)/ results
Jahmunah et al., 2019	19-channel EEG (14 normal and 14 Schizophrenia subjects)	Implementation of Gramian-Angular-Summation-Field (GASF), non-linear feature extraction and two-class classifier implementation	Traditional support vector machine classifier	Accuracy: ≈ 93
Xiang et al., 2019	Clinical-grade EEG data set	Assessment of schizophrenia class EEG based on the fuzzy-entropy (FE)	Positive and negative syndrome scale	The assessment of normal/disease class based on fuzzy entropy helped to attain improved statistical measures.
Chu, Huang, et al., 2017	International Affective Picture System database for images(for emotion). Participants(48 males, 52 females)	Computation of entropy to analyze 5 frequency bands	Support vector machine classifier	Accuracy: 81.5
Piryatinska et al., 2017	Publicly available database(45 schizophrenia patients, 39 normal	Estimation of complexity coefficients of original signals and the finite differences, out of bag estimation	Random forest classifier	Accuracy: 85.3
Thilakvathi et al., 2017	EEG recordings (78 schizophrenia patients and 23 normal)	Non-linear features extracted at rest and during mental activity.	-	Accuracy: 88.5
Reference	Database	Methodology: wavelet-based methods	Model/classifier used	Accuracy (%)/ Results
Sharma and Acharya, 2021	Institute of Psychiatry and Neurology in Warsaw(14 normal, 14 schizophrenia patients)	Wavelet-based feature extraction technique, computation of l1 norm features, 10-fold validation	K-nearest neighbour classifier	Accuracy: 99.21
Khare et al., 2021	Kaggle EEG data set (47 schizophrenia patients, 32 normal)	Continuous wavelet transform, short-time Fourier transform, smooth pseudo- Wigner-Ville distribution	Deep convolutional neural network	Accuracy: 93.36
Reference	Database	Methodology: decomposition of signals	Model/classifier used	Accuracy (%)/results
Baygin et al., 2021	Publicly available data sets (DB1: 14 schizophrenia patients, 14 normal, DB2: 49 schizophrenia patients, 32 normal)	Collatz pattern technique, maximum absolute pooling for decomposition	K-nearest neighbour classifier	DB1 data set Accuracy: 99.47
Tikka et al., 2021	EEG recordings (38 schizophrenia patients and 20 normal)	Wavelet decomposition, Mann–Whitney statistical test	Support vector machine	Accuracy: 78.95
Siuly et al., 2020	Kaggle ECG data set (47 schizophrenia patients, 32 normal)	Empirical mode decomposition, linear and non-linear feature extraction from intrinsic mode functions	Ensemble bagged tree classifier	Accuracy: 93.21
Reference	Database	Methodology: extraction of statistical features	Model/classifier used	Accuracy (%)/results
Sharma et al., 2020	(45 schizophrenia patients and 39 normal)	Higuchi fractal dimension, statistical features, leave-one-out validation	Support vector machine classifier	Accuracy: 71
Liu et al., 2017	Data from Shanghai hospital (40 high-risk patients, 40 schizophrenia patients, 40 normal)	Linear eigenvalue statistics	Support vector machine classifier	Accuracy: 90
Reference	Database	Methodology: other methods	Model/classifier used	Accuracy (%)/results
Olejarczyk and Jernajczyk, 2017;	19-channel EEG (14 normal and 14 Schizophrenia subjects	Computation of phase-locking value, phase-lag index, and directed transfer function	Graph based connectivity assessment	Correlation of EEG features with Schizophrenia condition.

TABLE 1 (Continued)

Reference	Database	Methodology: Non-linear feature extraction	Model/classifier used	Accuracy (%)/ results
EEG Database et al., 2017				
Dvey-Aharon et al., 2015	Clinical grade EEG data set	Detection and classification using the EEG attained from a single electrode	K nearest neighbour classifier	Accuracy: 88.7
Prabhakar et al., 2020	Institute of Psychiatry and Neurology in Warsaw (14 normal, 14 schizophrenia patients)	Feature extraction techniques with optimization techniques	Adaboost classifier	Accuracy: 98.7
Buettner et al., 2020	Institute of Psychiatry and Neurology in Warsaw (14 normal, 14 schizophrenia patients)	Granular division of EEG spectra, independent component analysis, 10-fold cross-validation	Random forest classifier	Accuracy: 96.7
Zhao et al., 2021	Zendo open access database(45 schizophrenia patients, 30 normal)	Partial directed coherence effective, phase lag index functional connectivity	Support vector machine classifier	Accuracy: ~ 95.2
Kim et al., 2015	Department of Psychiatry, Gongju National Hospital (90 schizophrenia patients, 90 normal)	Spectral analysis on five frequency bands, receiver operator characteristic curve	Receiver operating characteristic curve	Accuracy: 62.2
Li et al., 2019	EEG data recording using Symtop amplifier (23 schizophrenia patients, 25 normal)	Functional EEG networks, extraction of inherent spatial pattern of network, leave one out cross-validation	Support vector machine classifier	Accuracy: ~ 90.5
Bose et al., 2016	EEG data recording using EEG equipment Brain CMEEG-02, Brain Tech-40	Computation of absolute total power using Welch, Student's *t* test	Support vector machine classifier	Accuracy: 83.3
Devia et al., 2019	EEG recordings (11 schizophrenia patients and 9 normal)	EEG recordings of participants' free viewings of natural scenes, Wilcoxon rank sum test	Linear discriminant classifier	Accuracy: 71.0
Baradits et al., 2020	EEG recordings (70 schizophrenia patients and 75 normal)	Multivariate pattern analysis of microstate features, k-fold cross-validation	Support vector machine classifier	Accuracy: 82.7
Das and Pachori, 2021	Institute of Psychiatry and Neurology in Warsaw (14 normal, 14 schizophrenia patients)	Multivariate iterative filtering, decomposition of signals into multivariate intrinsic mode functions, feature extraction	Support vector machine classifier.	Accuracy: 98.9

TABLE 2 A summary of studies using machine learning methods with images for classification

Reference	Database	Methodology: other methods	Model/ classifier used	Accuracy (%)/results
Present study	19-channel EEG (14 normal and 14 Schizophrenia subjects)	Classification based on local configuration pattern image features and classifiers	K-nearest neighbour classifier	Accuracy: 97.2

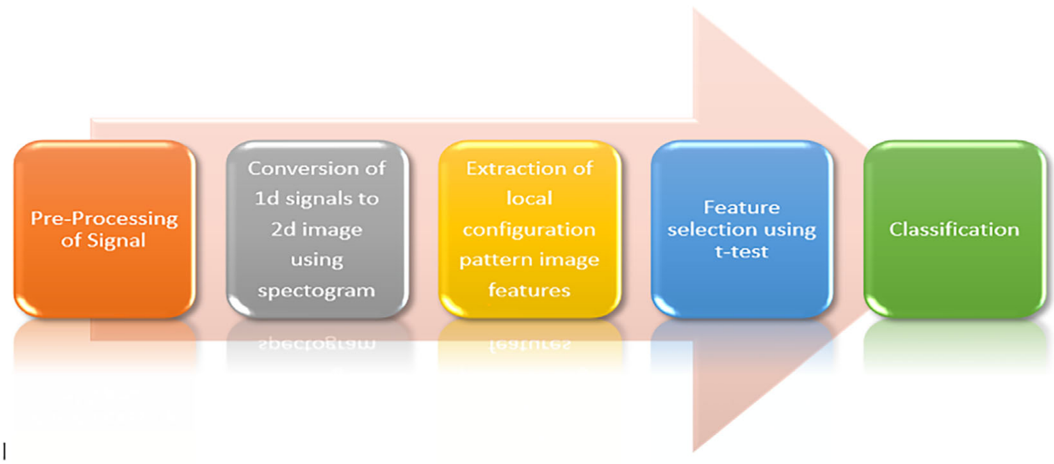

FIGURE 1 Various stages concerned with computer supported detection

of coefficients contained an approximation of the short-term and time-frequency information of the signals. Figures 3 and 4 show the spectrogram images of magnitude and angle of the normal and schizophrenia classes, obtained from channel 1 of the signals, respectively.

4.3 | Extraction of local configuration pattern features

LCP features were then extracted from the spectrograms. Among various image features, local binary patterns are very commonly used for extraction due to the low computational complexity and invariable rotations involved (Kwak et al., 2015). It works by forming a binary pattern based on the comparison of pixel grey-level patterns with its neighbours (Ojala et al., 2002). However, a drawback of this feature is that the intensity is approximated based on the computation of the average and variance of the neighbouring pixels. Hence, in this study, LCP features, which integrate local architectural and minuscule configuration information (Guo et al., 2011), were used. Considering neighbours $P = 8, 10, 12$ and radius $R = 2, 3, 4$, 81, 121 169 features were extracted from LCP, respectively, since using large neighbours may short change the LCP technique while approximating the reconstruction coefficients (Guo et al., 2011). Thus in this study, three different mappings: [(2, 8), (3, 10), (4, 12)] with small neighbours were extracted from each spectrogram, using LCP. The feature vector was concatenated to a single vector thereafter. Figure 5 shows the histograms (from the first channel out of the 19 channels) representing the LCP features for the three different mappings, for the normal and schizophrenia classes, respectively.

4.4 | Feature selection and validation

The 10-fold cross-validation technique (Kohavi, 1995) was used to evaluate the performance of classifiers wherein Student's *t*-test (Kim, 2015) and *z*-score standardization (Kranzusch et al., 2020) were computed per fold. Through the *t*-test, highly significant features were selected, and 10-fold was used to evaluate the classifiers.

4.5 | Implementation of classifiers

Classification of medical information is an essential process which helps to decrease the diagnosis burden. In machine learning and deep learning assessments, two-level and multi-level classifications are commonly executed to separate abnormal from normal information (Dey et al., 2019;

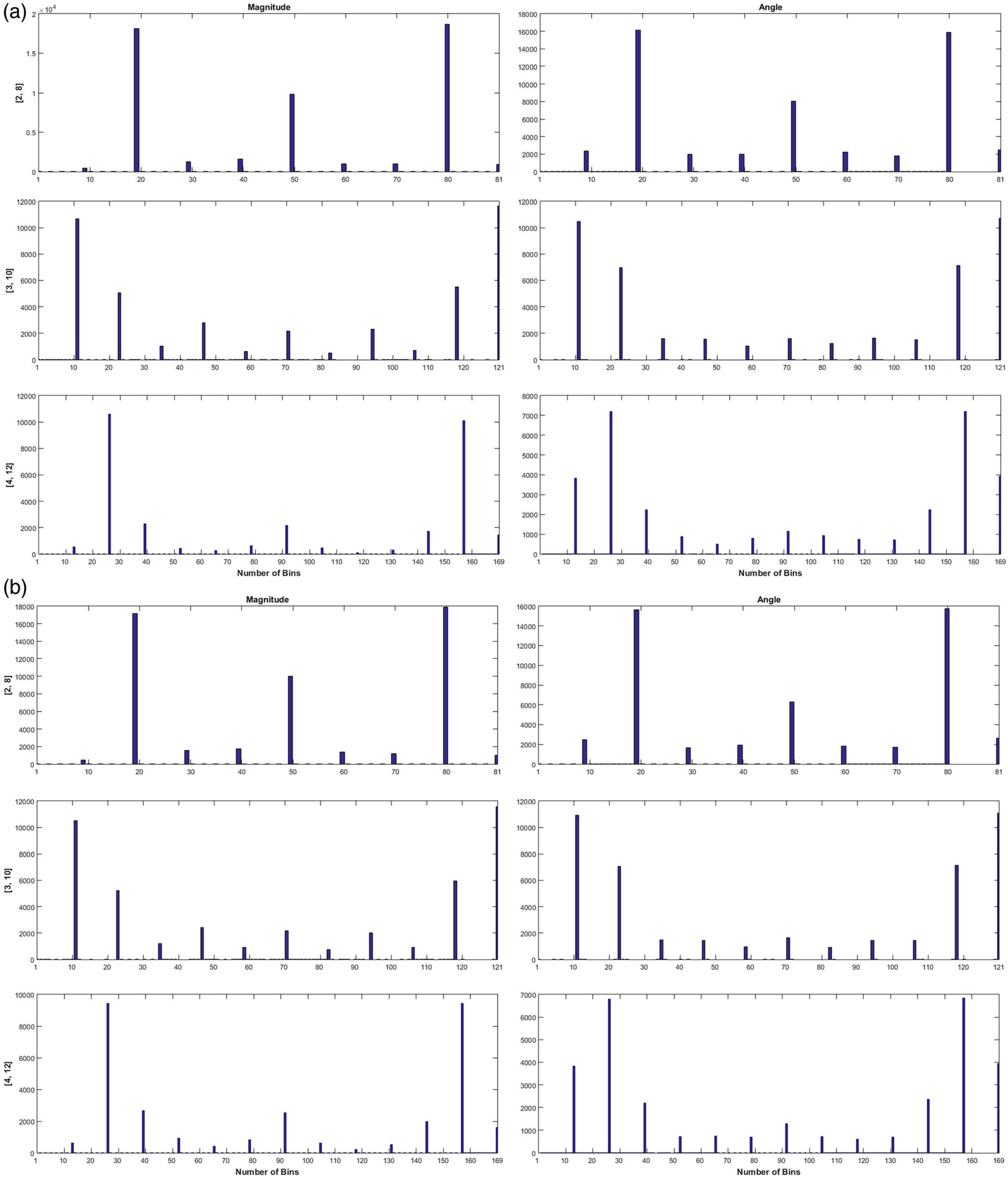

FIGURE 2 Multi-channel (19) EEG signals of (A) normal and (B) schizophrenia classes

Paul et al., 2019; Rajinikanth et al., 2018). This work also employs two-class classifiers, and the performances of these classifiers are confirmed based on the performance values (PV) and the confusion matrix. This work employs the following classifiers to segregate the existing EEGs into normal/schizophrenia groups.

TABLE 3 Information of the multi-channel EEG considered in this research

Type	Actual	Segmented EEG sequences
Normal	EEGs of 14 volunteers (211,250 samples/volunteer)	516 (6250/sequence)
Schizophrenia	EEGs of 14 volunteers (231,250 samples/volunteer)	626 (6250/sequence)
Total		1142 sequences

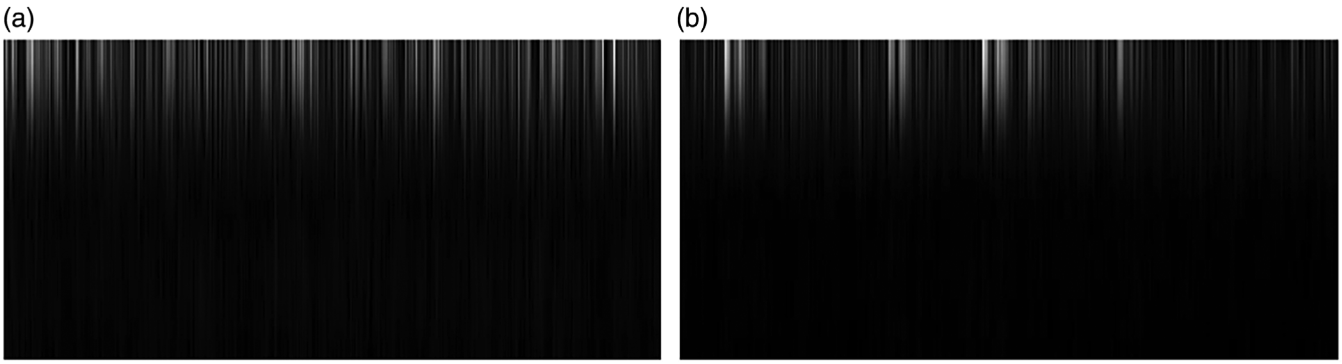

FIGURE 3 Spectrogram images of the magnitude of (a) normal and (b) schizophrenia classes obtained from channel 1

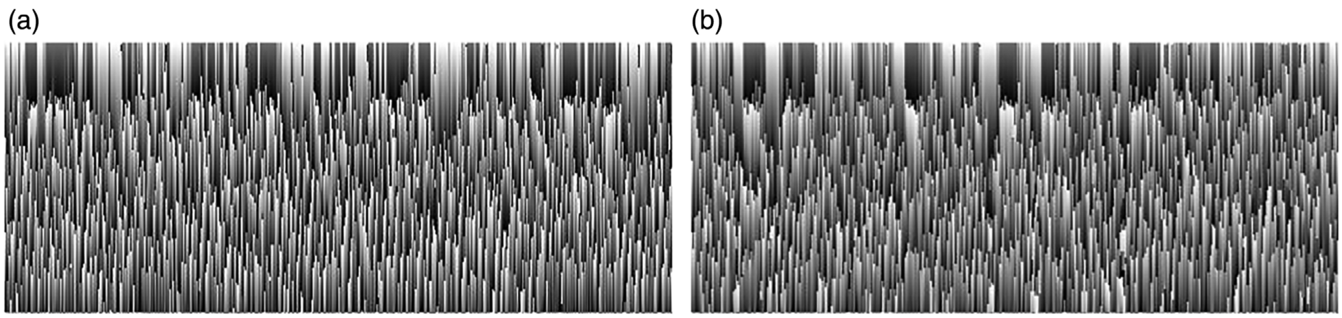

FIGURE 4 Spectrogram images of angle of (a) normal and (b) schizophrenia classes obtained from channel 1

4.5.1 | Decision tree

Decision tree (DT) is one of the generally considered classifiers to categorize linear and non-linear data with a series of testing schemes, which evolves as a tree resembling formation (Guan et al., 2019; Kotsiantis, 2013). DT utilizes a quality exploration setting as the root and interior nodes, and the class labels form the terminal nodes. Once a DT has been formed, categorization is achieved based on the decision taken in every limb in the tree. Other essential information regarding the DT considered to classify the EEG signals can be accessed from Aboalayo et al. (2016).

4.5.2 | Support-vector-machine

Support-vector-machine (SVM) classification is based on a hyperplane which categorizes the information according to the guiding features used during the training phases of the two and multi-class classification task (Acharya et al., 2012). The earlier works confirmed the implementation of SVM to classify the EEGs based on the considered features (Abe, 2003; Gautam & Ahmed, 2015; Sumithra et al., 2015). The proposed work considered the SVM with a linear/radial-basis-function (RBF) kernel. Furthermore, the SVM with other kernels, such as first order, second order and third order along with RBF, were used to classify the signals into normal/schizophrenia groups

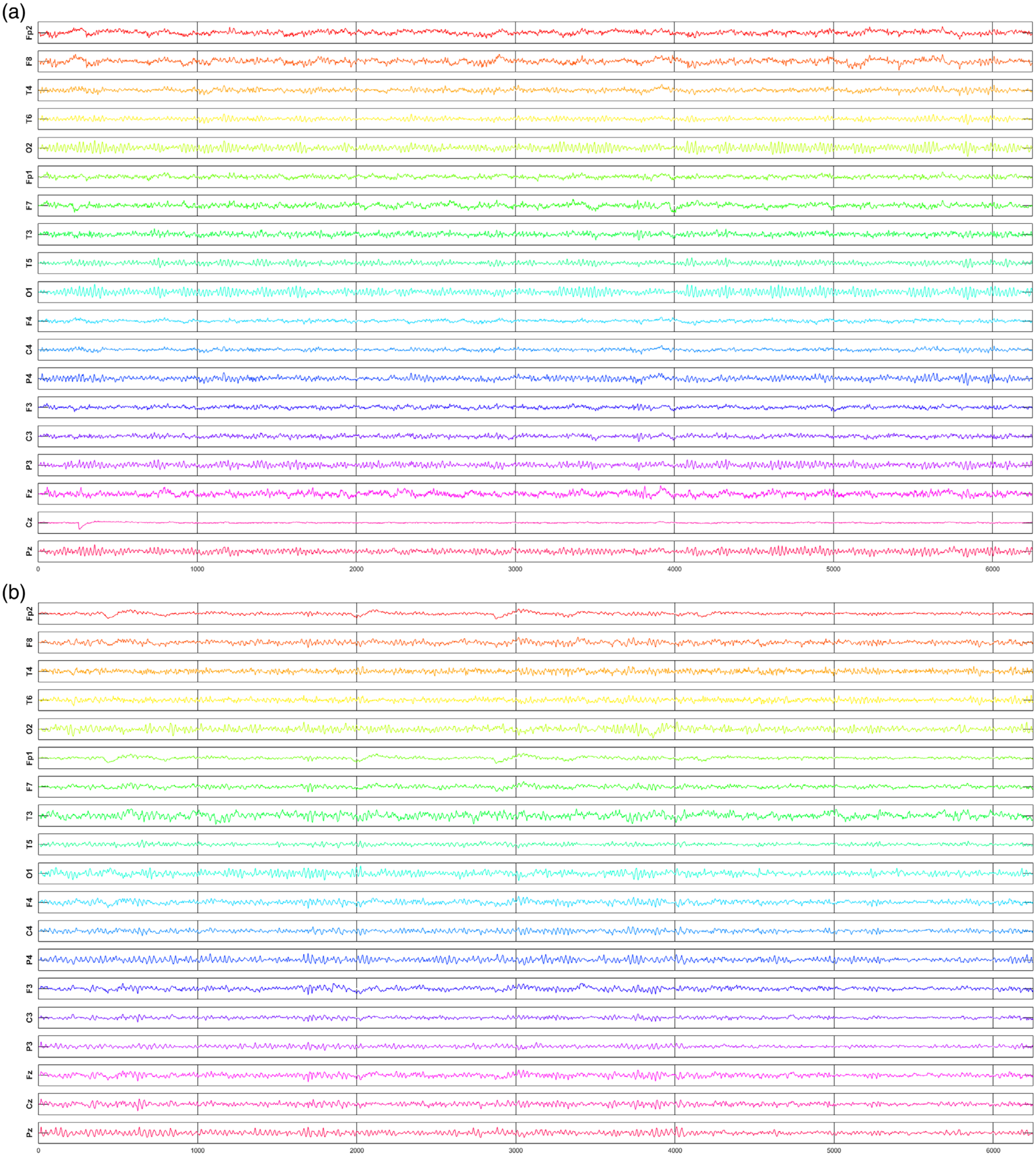

FIGURE 5 Histograms of angle and magnitude of (a) normal and (b) schizophrenia classes obtained from channel 1

4.5.3 | KNN

KNN classifies therapeutic information based on feature sets. In this work, the KNN ($K = 5$) is executed to categorize the EEG signals. Like other classifiers, the KNN also needs training and testing phases based upon the selected features. KNN evaluates the space among new features to each training feature, and discovers the best neighbour. Earlier work on KNN classification can be found in Kijsirikul and Ussivakul's (2002).

4.6 | Performance values and validation

Measures such as TP_{rate} (TPR), FP_{rate} (FPR), TN_{rate} (TNR) and FN_{rate} (FNR), are computed. From these values, other PMS, including accuracy (ACC), precision (PRE), sensitivity (SEN), specificity (SPE), positive predictive value (PPV) and F1 score are determined. For a satisfactory classifier, PVs, such as ACC, SEN, SPE and PPV should be maximized (approaching unity). The arithmetic expressions of these values are as follows (Fernandes et al., 2019; Wu et al., 2010)

$$\mathrm{TPR} = \mathrm{SEN} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{1}$$

$$\mathrm{TNR} = \mathrm{SPE} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \tag{2}$$

$$\mathrm{FNR} = \frac{\mathrm{FN}}{\mathrm{FN}+\mathrm{TP}} \tag{3}$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP}+\mathrm{TN}} \tag{4}$$

$$\mathrm{ACC} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \tag{5}$$

$$\mathrm{PRE} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{6}$$

$$\mathrm{F1S} = \frac{2\mathrm{TP}}{2\mathrm{TP}+\mathrm{FN}+\mathrm{FP}} \tag{7}$$

$$\mathrm{NPV} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FN}} \tag{8}$$

5 | RESULTS AND DISCUSSION

Table 4 presents the classification results. From the table, it is evident that the KNN classifier achieved the highest classification accuracy of 97.20%, performing better than other classifiers. This is shown in Figure 6, based on the validation of classifiers. From Table 1, it is apparent that Prabhakar et al. (Prabhakar et al., 2020) had obtained a higher accuracy of 98.77% as compared with our study. Although the size of data used by the authors is similar to our study, it is noteworthy that the backtracking search optimization algorithm they had used is computationally intensive as compared with our proposed method. Hence, our method is more effective for rapid diagnosis of schizophrenia. Similarly, Sharma et al. (Sharma & Acharya, 2021) had obtained a slightly higher accuracy of 99.21% as compared with our study, using a similar data size to our study. However, it is apparent that employing local configuration patterns as in our study is less computationally intensive (Kwak et al., 2015) whereas wavelet-based feature extraction methods are more computationally intensive (Silva, 2015). Baygin et al. (2021) and Sharma and Acharya (2021) had also yielded higher classification accuracies. Although the authors had used a larger data size to train and test their developed models, as compared to our study, their proposed techniques may be more computationally intensive as compared to ours. Das and Pachori (2021) had also

TABLE 4 Performance of the classifiers based on extracted features

Classifier scheme	ACC (%)	SEN (%)	SPE (%)	PPV (%)
SVM-RBF	93.96	90.25	98.45	98.61
K-nearest neighbours (KNN)	97.20	96.81	97.67	98.07
SVM with second order kernel (SVM2)	95.97	94.72	97.48	97.90
SVM with third order kernel (SVM3)	96.23	94.88	97.86	98.22
SVM with first order kernel (SVM1)	92.82	88.34	98.25	98.41
Decision tree (DT)	90.20	92.01	88.01	90.36

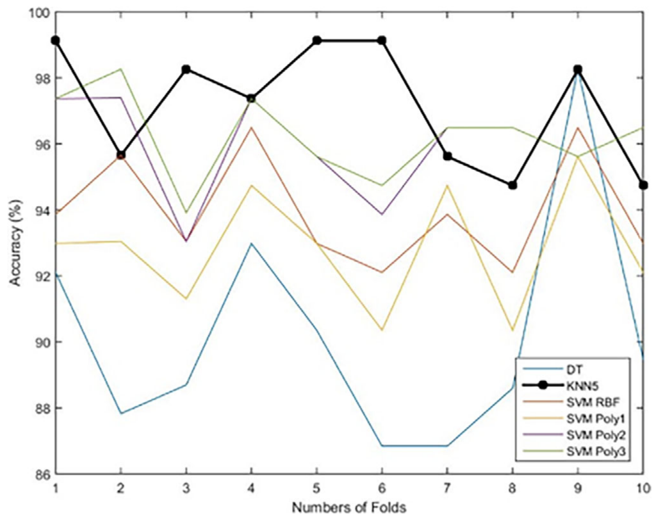

FIGURE 6 Number of fold versus accuracy plot

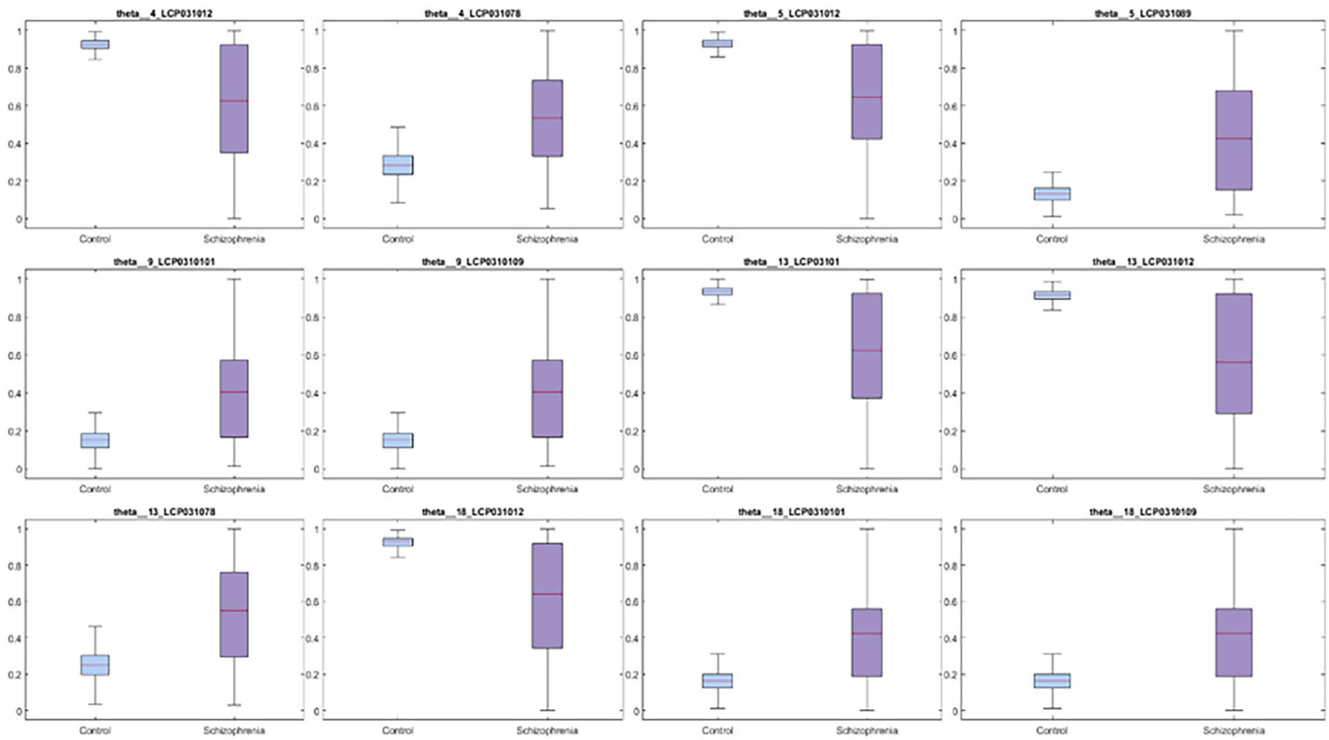

FIGURE 7 Boxplot of the unique top five features per fold

achieved a higher accuracy, but they had employed multivariate iterative filtering and the decomposition technique which is more is computationally intensive as compared to our proposed method. While the other studies had achieved lower accuracies for the machine learning techniques they had explored, Olejarczyk and Jernajczyk (2017), Ibáñez-Molina et al. (2018) and Xiang et al. (2019) had discussed only qualitative results. Thus, it is evident that our proposed technique is able to perform better. Figure 7 presents the boxplot of the five unique top features per fold, wherein the five features appear in at least one fold, were extracted for the boxplot. These features fall under 12 boxplots, hence there are 12 plots in Figure 7. Table A1 shows the best performing LCP features wherein, the top five features from the local configuration patterns are LCP 03101, LCP031012, LCP031078, LCP031012 and LCP031089. From the confusion matrix, as seen in Figure 8, it is notable that the misclassification rate of the KNN classifier is only 1.97% for normal images and 0% for schizophrenia images. The low misclassification rate and highly discriminatory features extracted, attest to the robustness of our proposed technique.

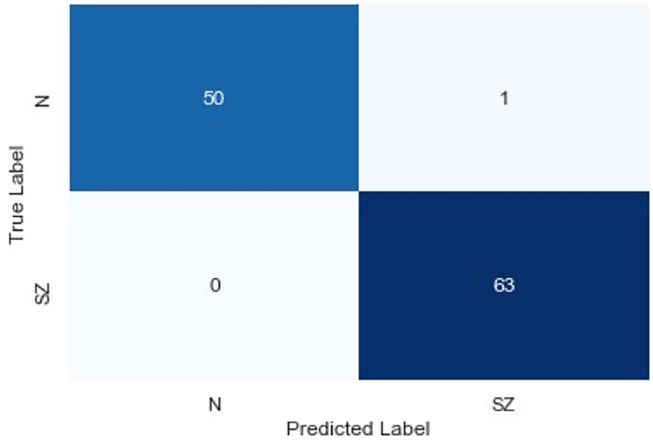

FIGURE 8 Confusion matrix of K-nearest neighbour classifier

Naira and Del Alamo (2019), Oh et al. (2019), and Nikhil et al. (2021), Phang et al. (2019), Phang et al. (2020), Sun et al. (2021), Singh et al. (2020), Shalbaf et al. (2020), Aslan and Akin (2020), Chu, Qiu, et al. (2017), Calhas et al. (2020), Ahmedt-Aristizabal et al. (2021) and Shoeibi et al. (2021) on the other hand, had employed deep learning algorithms for the classification of schizophrenia, mostly achieving high classification accuracies of above 90%, wherein Oh et al. (2019), Nikhil et al. (2021), Sun et al. (2021), Singh et al. (2020), Shalbaf et al. (2020) and Shoeibi et al. (2021) had yielded higher accuracies than our study. As part of future work, deep learning models could be explored as a classifier for the spectrogram images. There are several advantages and disadvantages of our technique, listed below.

5.1 | Advantages

1. The proposed method has been evaluated by 10-fold validation, hence it is robust.
2. A rapid diagnosis of schizophrenia is possible with our recommended system due to its reduced computational complexity.
3. Extracting local configuration pattern features from the spectrogram images allows us to obtain a high accuracy of 97.20%.

5.2 | Disadvantages

1. Only a small data size can be used for this technique.
2. The classification and selection of features is done manually.

6 | CONCLUSION AND FUTURE WORK

The aim of this work was to develop a system for CSD of schizophrenia from the multi-channel EEG. This research incorporated clinical grade EEG signals from 28 volunteers (14 normal and 14 schizophrenia patients) recorded using a 19-channel electrode array. Initially, a segmentation task was implemented to extract the EEG with 6250 discretized sample points (25 s duration). Thereafter, the 1D EEG signals were converted to 2D images using the spectrogram. LCP features were extracted from the grey images subsequently. Highly discriminatory features were selected with Student's *t*-test. This feature set was then input to several classifiers. The extracted features were split into 10-folds for classification, and Student's *t*-test and a *z*-score standardization were used per fold. The experimental outcome confirmed that the KNN classifier offered a superior result (classification accuracy = 97.20%) as compared to other related classifiers considered in this study. The overall results have confirmed that the proposed technique works well on clinically acquired EEG signals, and this approach is significant for diagnosing schizophrenia based on signal composition. This is one of the earliest studies to extract local configuration pattern features from the spectrogram images, obtaining a high accuracy of 97.20% with reduced computational complexity. Larger data set containing high or low-risk for schizophrenia, motivates future work involving deep learning model.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in EEG Database (Olejarczyk, E.; Jernajczyk, W) at http://dx.doi.org/10.18150/repod.0107441. These data were derived from the following resources available in the public domain: - EEG Database (Olejarczyk, E.; Jernajczyk, W), http://dx.doi.org/10.18150/repod.0107441.

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APPENDIX A

TABLE A1 Range(mean ± *SD*) of best-performing LCP features

	Control		Schizophrenia		
	Mean	*SD*	Mean	*SD*	*p*-value
theta__13_LCP03101	1.8223	0.0191	1.6563	0.1558	0.0000
theta__13_LCP031012	1.6122	0.0148	1.4693	0.1348	0.0000
theta__13_LCP031078	0.7616	0.0199	0.8322	0.0637	0.0000
theta__5_LCP031012	1.6218	0.0136	1.4836	0.1316	0.0000
theta__5_LCP031089	0.5828	0.0164	0.6824	0.0940	0.0000
theta__9_LCP0310101	0.3434	0.0399	0.5213	0.1654	0.0000
theta__9_LCP0310109	0.3434	0.0399	0.5213	0.1654	0.0000
theta__4_LCP031012	1.6176	0.0146	1.4825	0.1291	0.0000
theta__18_LCP031012	1.6141	0.0161	1.4755	0.1326	0.0000
theta__16_LCP031012	1.6135	0.0158	1.4730	0.1346	0.0000
theta__17_LCP031012	1.6116	0.0145	1.4773	0.1291	0.0000
theta__4_LCP031078	0.7571	0.0218	0.8275	0.0638	0.0000
theta__18_LCP0310101	0.3625	0.0419	0.5355	0.1612	0.0000
theta__18_LCP0310109	0.3625	0.0419	0.5355	0.1612	0.0000
theta__3_LCP031012	1.6111	0.0147	1.4778	0.1283	0.0000
theta__19_LCP031012	1.6128	0.0162	1.4746	0.1332	0.0000
theta__8_LCP031012	1.6149	0.0130	1.4844	0.1265	0.0000
theta__8_LCP0310101	0.3625	0.0369	0.5444	0.1728	0.0000
theta__8_LCP0310109	0.3625	0.0369	0.5444	0.1728	0.0000
theta__19_LCP03101	1.8229	0.0196	1.6633	0.1544	0.0000
theta__9_LCP031012	1.6189	0.0137	1.4829	0.1322	0.0000
theta__17_LCP03101	1.8245	0.0167	1.6691	0.1511	0.0000
theta__18_LCP03101	1.8274	0.0199	1.6672	0.1555	0.0000
theta__19_LCP031089	0.5876	0.0160	0.6853	0.0942	0.0000

(Continues)

TABLE A1 (Continued)

	Control		Schizophrenia		
	Mean	*SD*	Mean	*SD*	*p*-value
theta__13_LCP031089	0.5879	0.0165	0.6884	0.0970	0.0000
theta__16_LCP03101	1.8226	0.0185	1.6600	0.1584	0.0000
theta__16_LCP031089	0.5862	0.0165	0.6860	0.0964	0.0000
theta__4_LCP03101	1.8260	0.0165	1.6745	0.1479	0.0000
theta__18_LCP031089	0.5850	0.0163	0.6830	0.0948	0.0000
theta__13_LCP0310100	0.4289	0.0069	0.5293	0.0990	0.0000
theta__3_LCP03101	1.8240	0.0166	1.6734	0.1477	0.0000
theta__14_LCP031012	1.6106	0.0143	1.4796	0.1286	0.0000
theta__19_LCP031078	0.7614	0.0209	0.8303	0.0641	0.0000
theta__18_LCP031078	0.7537	0.0190	0.8234	0.0657	0.0000
theta__14_LCP0310101	0.3726	0.0414	0.5392	0.1588	0.0000
theta__14_LCP0310109	0.3726	0.0414	0.5392	0.1588	0.0000
theta__5_LCP031078	0.7611	0.0241	0.8310	0.0640	0.0000
theta__12_LCP031012	1.6089	0.0173	1.4718	0.1347	0.0000
theta__10_LCP031078	0.7608	0.0236	0.8289	0.0625	0.0000
theta__4_LCP031089	0.5825	0.0175	0.6799	0.0948	0.0000
theta__7_LCP0310101	0.3805	0.0419	0.5458	0.1576	0.0000
theta__7_LCP0310109	0.3805	0.0419	0.5458	0.1576	0.0000
theta__9_LCP031078	0.7552	0.0230	0.8255	0.0652	0.0000
theta__5_LCP031023	1.4175	0.0187	1.3206	0.0941	0.0000
theta__7_LCP031012	1.6099	0.0148	1.4841	0.1241	0.0000
theta__8_LCP03101	1.8283	0.0153	1.6803	0.1466	0.0000
theta__13_LCP0310111	0.2286	0.0070	0.3182	0.0891	0.0000
theta__16_LCP031078	0.7614	0.0220	0.8304	0.0645	0.0000
theta__12_LCP03101	1.8212	0.0202	1.6635	0.1562	0.0000
theta__9_LCP031089	0.5798	0.0150	0.6776	0.0964	0.0000
theta__5_LCP03101	1.8239	0.0170	1.6726	0.1505	0.0000
theta__10_LCP031012	1.6210	0.0158	1.4895	0.1307	0.0000
theta__10_LCP031089	0.5829	0.0146	0.6778	0.0939	0.0000
theta__14_LCP03101	1.8239	0.0163	1.6730	0.1504	0.0000
theta__9_LCP031023	1.4160	0.0183	1.3200	0.0944	0.0000
theta__17_LCP031078	0.7569	0.0193	0.8229	0.0631	0.0000
theta__3_LCP0310101	0.3701	0.0415	0.5508	0.1764	0.0000
theta__3_LCP0310109	0.3701	0.0415	0.5508	0.1764	0.0000
theta__17_LCP0310101	0.3690	0.0394	0.5318	0.1586	0.0000
theta__17_LCP0310109	0.3690	0.0394	0.5318	0.1586	0.0000
theta__16_LCP031023	1.4086	0.0177	1.3126	0.0951	0.0000
theta__9_LCP031090	0.2037	0.0759	0.4171	0.1989	0.0000
theta__9_LCP031098	0.2037	0.0759	0.4171	0.1989	0.0000
theta__3_LCP0310100	0.4300	0.0076	0.5225	0.0931	0.0000
theta__13_LCP03103	0.1820	0.0422	0.3218	0.1338	0.0000
theta__13_LCP03109	0.1820	0.0422	0.3218	0.1338	0.0000
theta__13_LCP031023	1.4056	0.0165	1.3103	0.0949	0.0000
theta__11_LCP031012	1.6080	0.0155	1.4814	0.1273	0.0000
theta__17_LCP031089	0.5894	0.0176	0.6819	0.0920	0.0000

TABLE A1 (Continued)

	Control		Schizophrenia		
	Mean	*SD*	Mean	*SD*	*p*-value
theta__5_LCP0310100	0.4253	0.0086	0.5197	0.0955	0.0000
theta__16_LCP0310100	0.4284	0.0066	0.5274	0.1005	0.0000
theta__7_LCP03101	1.8223	0.0173	1.6801	0.1440	0.0000
theta__9_LCP03101	1.8287	0.0171	1.6738	0.1571	0.0000
theta__3_LCP031089	0.5894	0.0187	0.6818	0.0922	0.0000
theta__4_LCP031023	1.4126	0.0195	1.3186	0.0936	0.0000
theta__4_LCP0310100	0.4263	0.0080	0.5186	0.0940	0.0000
theta__5_LCP031092	0.1361	0.0591	0.3520	0.2117	0.0000
theta__5_LCP031096	0.1361	0.0591	0.3520	0.2117	0.0000
theta__4_LCP0310101	0.3452	0.0463	0.5269	0.1794	0.0000
theta__4_LCP0310109	0.3452	0.0463	0.5269	0.1794	0.0000
theta__18_LCP031023	1.4076	0.0175	1.3141	0.0941	0.0000
theta__6_LCP031012	1.6023	0.0166	1.4807	0.1235	0.0000
theta__18_LCP0310100	0.4277	0.0072	0.5238	0.0985	0.0000
theta__19_LCP031023	1.4056	0.0173	1.3134	0.0930	0.0000
theta__3_LCP0310111	0.2281	0.0070	0.3080	0.0819	0.0000
theta__8_LCP031023	1.4082	0.0171	1.3211	0.0877	0.0000
theta__19_LCP0310100	0.4289	0.0066	0.5252	0.0990	0.0000
theta__17_LCP0310100	0.4286	0.0079	0.5221	0.0959	0.0000
theta__17_LCP031023	1.4043	0.0167	1.3148	0.0904	0.0000
theta__12_LCP0310100	0.4303	0.0084	0.5273	0.0998	0.0000
theta__11_LCP03101	1.8208	0.0178	1.6767	0.1482	0.0000
theta__8_LCP031089	0.5866	0.0163	0.6758	0.0910	0.0000
theta__10_LCP031023	1.4169	0.0206	1.3240	0.0937	0.0000
theta__2_LCP031012	1.6025	0.0178	1.4808	0.1251	0.0000
theta__6_LCP0310101	0.3938	0.0416	0.5434	0.1489	0.0000
theta__6_LCP0310109	0.3938	0.0416	0.5434	0.1489	0.0000
theta__11_LCP031078	0.7592	0.0195	0.8220	0.0618	0.0000
theta__6_LCP03101	1.8164	0.0181	1.6773	0.1437	0.0000