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Automated detection of schizophrenia using nonlinear signal processing methods

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ABSTRACT

Examination of the brain's condition with the Electroencephalogram (EEG) can be helpful to predict abnormality and cerebral activities. The purpose of this study was to develop an Automated Diagnostic Tool (ADT) to investigate and classify the EEG signal patterns into normal and schizophrenia classes. The ADT implements a sequence of events, such as EEG series splitting, non-linear features mining, *t*-test assisted feature selection, classification and validation. The proposed ADT is employed to evaluate a 19-channel EEG signal collected from normal and schizophrenia class volunteers. A dataset was created by splitting the raw 19-channel EEG into a sequence of 6250 sample points, which was helpful to produce 1142 features of normal and schizophrenia class patterns. Non-linear feature extraction was then implemented to mine 157 features from each EEG pattern, from which 14 of the principal features were identified based on significance. Finally, a signal classification practice with Decision-Tree (DT), Linear-Discriminant analysis (LD), k-Nearest-Neighbour (KNN), Probabilistic-Neural-Network (PNN), and Support-Vector-Machine (SVM) with various kernels was implemented. The experimental outcome showed that the SVM with Radial-Basis-Function (SVM-RBF) offered a superior average performance value of 92.91% on the considered EEG dataset, as compared to other classifiers implemented in this work.

1. Introduction

Malfunction of the brain by disease or disorder affects normal activity in humans [1–3]. Schizophrenia(sz) is a chronic disorder which affects the thinking ability as well as general behavior. The report of the World Health Organization (WHO) substantiates that sz is a severe mental disorder, and more than 21 million people worldwide are affected by it [4]. Yet, WHO has also stated that sz is treatable, and early or post diagnosis may be helpful to identify its severity and stage. Detection and treatment of sz is essential in patients, since it creates substantial inconvenience in regard to thinking, memory, perception, and other living activities. If left untreated, it is an unalterable process which damages the human behavioral abilities in its later stages [5]. Early as well as post discovery of sz may help during implementation of possible treatment methods to cure or limit the effects. Most mental disorders such as sz can be assessed by signaling [7] or imaging techniques [6]. Recently, a number of non-invasive techniques have been proposed and implemented by investigators to identify sz based on the Electroencephalogram(EEG) acquired using multi-channel sensor arrays [8,9]. The assessment and confirmation accuracy of sz from the EEG pattern depends mainly on the tool considered to examine these signals.

The imaging techniques, such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), are costly and require additional recording and computational time as compared to signaling procedures such as EEG [10–13]. An EEG signal acquired using an appropriate electrode can be useful to reveal essential detail regarding brain activity, and examination of these signals may help to detect the condition of the brain [14,15,25]. During the clinical diagnostic process, the EEG is obtained by placing the electrodes at predefined scalp

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Table 1
Summary of ADT systems using EEG for the classification of Schizophrenia.

Authors	umber of features	Techniques	Number of participants	Conclusion
Kim et al. [26]	–	● Spectral power of EEG computed with Fast Fourier Transformation using MATLAB(covariates) ● Delta, Theta, Alpha 1 and 2, Beta frequency bands analysed. ● ANOVA, ROC analysis. ● QEEG parameters	Normal: 90 healthy subjects sz: 90 patients	**Best classification Acc:** Delta frequency band, 62.2%.
Dvey-Aharon et al. [20]	–	● Time-frequency transformation ● Feature-Optimisation ● Beta2 band frequencies ● Leave one out cross validation	Normal: 25 healthy subjects sz: 25 patients	**Best electrode**: F2 **Best electrodes that differentiate the 2 classes**: F2,FC3 **Classification** Acc: between 91.5% and 93.9%.
Johannesen et al. [27]	60 features per participant	● Theta 1 and 2, alpha, beta and gamma frequency bands analysed during a working memory task. ● Brain Vision Analyser software to analyse signals ● SVM to build EEG classifiers ● Regression-based analyses used to validate SVM models.	Normal: 12 healthy subjects sz: 40 patients	**Model 1:** Achieved 84% accuracy in classifying healthy individuals and 74% upon cross-validation with s data. **Model 2**: Achieved 87% classification accuracy in discriminating healthy and sz patients, with frontal theta at baseline and frontal alpha during retrieval identified as key classifiers of sz diagnosis.
Santos-Mayo et al. [28]	20 per subject	● P3b brain signals ● Time, frequency domain features ● Channel grouping ● J5, MIFS or DISR feature selection algorithms ● SVM, Multilayer perceptron(MLP) classifiers	Normal: 31 healthy subjects sz: 16 patients	**Using 15 Hz-J5-MLP** Acc: 93.42% Sen: 87.27% Spe: 96.73% **Using 35 Hz-J5-SVM** Acc : 92.23% Sen: 88.38% Spe: 94.99%
Ibanez-Molina et al. [8]	–	● EEG signals analysed at rest and during picture naming. ● Neuroscan SynAmps 32-channel amplifier. ● Lempel-Ziv Complexity(LZC), Multiscale LZC. ● Feature selection using J5, MIFS, DISR.	Normal: 17 healthy subjects sz: 18 patients	Healthy subjects had lesser errors made compared to patients. Higher complexity values were found inpatients, in right frontal regions at rest but no differences were found between the 2 groups during the naming activity. Higher complexity values were observed in sz patients at rest, compared to at task.
V. Jahmunah et al. [51]	–	● 11-layered CNN model ● Non-subject base testing, subject base testing ● k-fold validation, 10-fold validation	Normal: 14 healthy subjects sz: 14 patients	**Non-subject base testing** Acc : 98.07% **Subject base testing** Acc : 81.26%
Present work	14	● EEG series splitting ● Non-linear feature mining ● Feature selection using t-test ● Classification using DT, LD, kNN, PNN, SVM classifiers	Normal: 14 healthy subjects sz: 14patients	**Best classification ACC:** SVM RBF classifier with an accuracy of 92.91% compared to other classifiers.

ACC – accuracy, SEN - sensitivity, SPE - specificity, PPV- positive predictive value.

sections. Recently, EEG patterns were extensively used to inspect for maladies such as dementia, Alzheimer's disease, sleep disorder, epilepsy, sz, Parkinson's disease and other brain related disorders [16,17,21,23,52,53].

Recent studies provide insights to the classification of sz based on EEG patterns [18]. Table 1 highlights the summary of ADT systems employed for the detection of sz using EEG signals. Kim et al. [26] extracted EEG signals from 21 gold cup electrodes, positioned according to the 10–20 international standards. Horizontal and vertical eye movements of participants were studied. After pre-processing, five frequency bands were chosen for analysis. For each of the five bands, the spectral power of the EEG was computed using Fast Fourier Transformation, after which the Analysis of Variance(ANOVA) method was employed to study EEG power deviations. The Receiver Operating Curve (ROC) analysis technique was used to determine the diagnostic performance of a test, utilized in distinguishing between normal and sz patients. The highest classification accuracy of 62.2% was obtained for delta power. Dvey-Aharon et al. [20] discussed a Time-Frequency transformation based evaluation of the EEG signal to examine for sz. In this work, a Stockwell approach was implemented to convert the EEG signal into an image, and then feature extraction and classification procedures were incorporated to attain improved results. The top five unique electrodes were reported to have a prediction accuracy between 92.0% and 93.9%, with F2 portraying to be the best electrode. Johannesen et al. [27] acquired EEG recordings from participants using a 64 electrode system. Participants were required to press one of two response buttons, using either their right or left index finger, to indicate whether a particular letter was presented in the previous set. The signals were analysed using the Brain Vison Analyser software and segmented via four stages of processing: pre-stimulus baseline, encoding, retention and retrieval. At each of the four stages of processing, time-frequency data(squared wavelet coefficients, binned and averaged according to correct versus incorrect response accuracy) was retrieved for the five frequency bands examined. Statistical analyses were conducted on spectral power measured at the Frontal, Central and Occipital locations. Feature selection was done using the wrapper method [22]. The 1-norm Support Vector Machine (SVM) classifier was utilized to classify correct and incorrect trials in data with the SVM Model 1, achieving a classification accuracy of 84%. The SVM Model 2 was implemented to classify normal versus the sz condition in correct trial data, achieving a classification accuracy of 87%. Santos-Mayo et al. [28] analysed the EEG-ERP signals of participants who were involved in an auditory task. The Brain Vision equipment, in compliance with the 10–20 international standards, was used to record the brain signals. After acquisition, the signals were pre-processed using EGGLAB [24], after which 16 time-domain features and four frequency-domain features were extracted per electrode, for each participant. Features were selected via linear discriminant analysis using J5 and Mutual Information Feature Selection(MIFS) coupled with the Double Input Symmetrical Relevance (DISR). The Multilayer Perceptron(MLP) and SVM classifiers were employed for classification. High classification rates of 93.42% and 92.23% were achieved with the J5 MLP and J5 SVM classifiers, respectively. Ibáñez-Molina et al. [8] also implemented sz examination based on the EEG. In this work, EEG recordings were extracted from participants while they were at rest and engaged in a naming task. The Neuroscan SynAmps 32-channel amplifier was employed for data acquirement. EEG signals at the resting phase were acquired prior to the task, while those from the task were extracted after each trial. In the resting phase, the segments were analysed using a moving window method, after which LZC was computed per window. After normalisation, the final LZC value was computed by calculating the average of the values obtained from the moving window method. A total of 80 EEG segments of 2×10^3ms were evaluated, at task, and then averaged to obtain the final Multiscale LZC value. Higher complexity values were reported in right frontal regions of patients who were at rest. V. Jahmunah et al. [51], developed an eleven-layered deep learning model for the classification of sz. Two CNN models were developed separately for subject base testing and non-subject base testing. In subject base testing, validation of the system was carried out in three phases: training, testing and validation of data. During training, k-fold validation was used, whereby the entire data was split into fourteen equal parts. Twelve parts were used for training, one was used for validation and another for testing. In non-subject base testing, 10-fold validation was conducted during training and the system was evaluated through the training and testing phases. Accuracies of 98.07% and 81.26% were yielded for non-subject base testing and subject base testing, respectively.

2. Data used

Fifteen minutes of EEG signals acquired from 14 patients with paranoid sz, encompassing seven males and seven females, with a mean age of 27.9 ± 3.3 and 28.3 ± 4.1 years, respectively, were collected from the Institute of Psychiatry and Neurology in Warsaw, Poland [19]. Fourteen healthy subjects within similar age and gender ratio were recruited from the same institute. In this study, a multi-channel (19-channel) EEG was adopted for the assessment. The electrodes used were Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1 and O2. Fifteen minutes of EEG signals were recorded from the participants at a sampling rate of 250 Hz, as they remained in a composed state with eyes closed. Table 2 details the EEG segments studied from the two classes. The sample EEG signal of normal and sz cases are depicted in Fig. 1. Fig. 1(a) presents the normal EEG signal, which shows enhanced amplitude values in most of the channels, as compared to the sz signals depicted in Fig. 1(b).

3. Methodology

3.1. Pre-processing

Thirty second segments without artefacts were used for analysis. A 2^{nd} order Butterworth filter was employed to preprocess the extracted EEG signals. The signals were segmented into nonoverlapping segments of 25 s, such that each segment consisted of 6250×19 sample points. This segmentation gave rise to 1142 EEG patterns, which were then grouped to form a new database of normal and sz class EEGs with a fixed length. Following segmentation, 12 features were extracted from the signals. Fig. 2 presents the paradigm employed in this work to examine the EEG signals.

3.2. Feature extraction and selection

157 nonlinear features were extracted from both EEG classes. The optimal feature set of 14 features were then selected from the 157 features using Student's *t*-test [29]. The features employed are the activity entropy(ae), largest Lyapunov exponent(lx) [30], Kolmogorov-Sinai(k-s) entropy [31], Hjorth complexity(hc) and mobility(hm) [32,33], Rényi(re) [34], Shannon(sn) [35], Tsallis(ts) [36], Kolmogorov complexity(kc) [37], bispectrum (entropy 1, 2 and phase)(bs) [38], cumulant(c) [39] and permutation entropy(pe) [40]. Fig. 3 shows the sample recurrence plots [47–50] for (a) normal and (b) sz EEG signals.

Table 2
Total number of EEG patterns considered in this study.

Type	Number of EEG segments
Normal	516
Schizophrenia	626
Total	1142

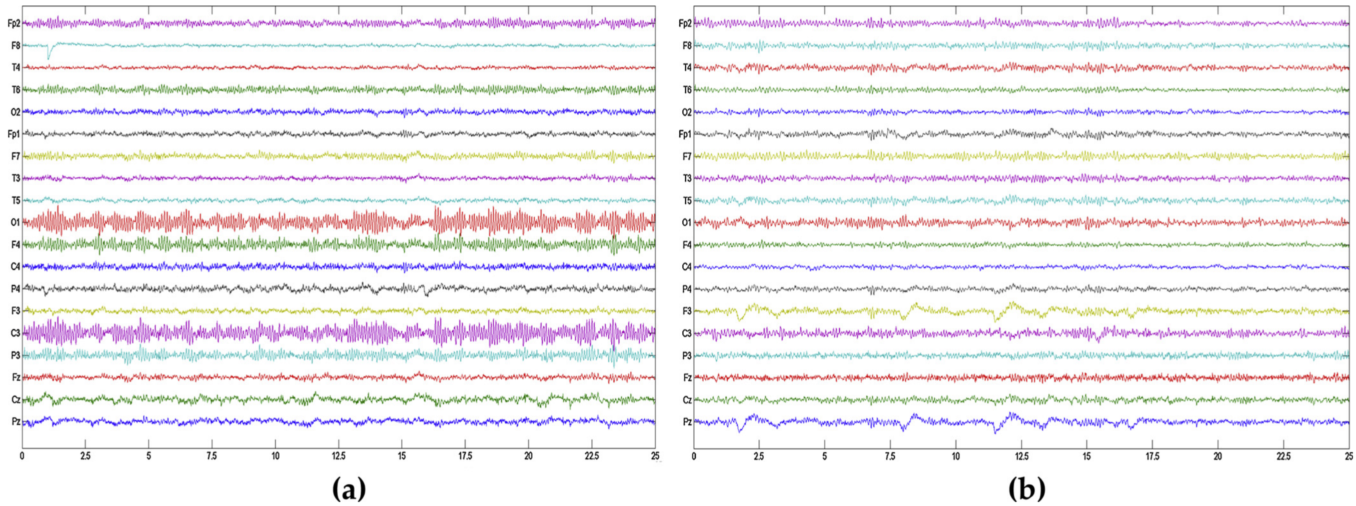

Fig. 1. Pre-processed EEG signals of (a) normal and (b) schizophrenia.

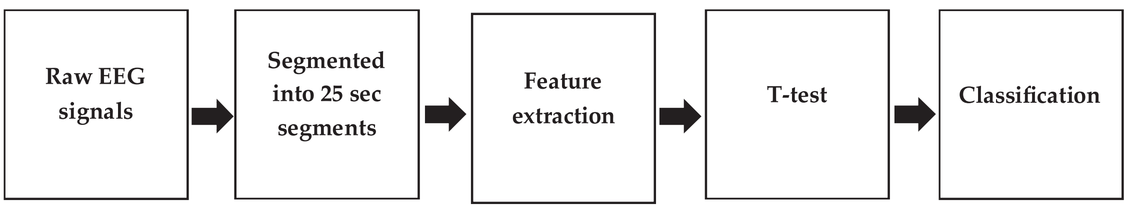

Fig. 2. Organization of the proposed automated tool to detect Schizophrenia.

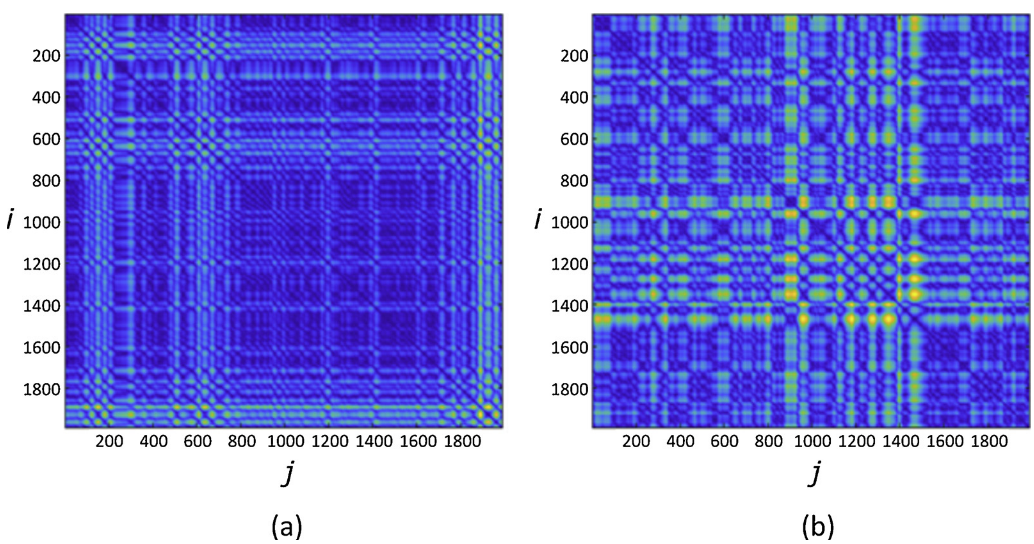

Fig. 3. Recurrence plots of (a) Normal and (b) Schizophrenia EEG signals.

3.3. *Classification*

Various classifiers were exploited to distinguish between the two classes. The Decision Tree (DT) classifier [41], which implements a tree-like configuration with a series of test sequences, was used. The Linear Discriminant analysis (LD) classifier, which identifies a matching category according to a set of values or findings, was also implemented [42,43]. The K-Nearest Neighbour (KNN) is another classifier that was considered in this work [44]. Like other classifiers, the KNN requires training and testing based on the available dominant features. The Probabilistic Neural Network (PNN) was an additional classifier implemented. In PNN [45,46], the hidden-layer is used to compute a probability density value, and the summing-layer accumulates the result. The SVM classifier with Radial-Basis-Function (SVM-RBF) was also used to classify the EEGs based on the selected features. Moreover, the SVM with various polynomial kernels, including 1st order (SVM1), 2nd order (SVM2) and 3rd order (SVM3), were also instituted to classify normal versus sz EEG signal datasets. The statistical metrics: accuracy (Acc), sensitivity(Sen), specificity(Spe) and positive predictive value (Ppv) were utilized to gauge the performance of the adopted classifiers.

4. Results

Table 3 illustrates the 14 significant features identified with the *t*-test. The features were ranked based on the p-values. The Hjorth complexity, with the lowest p-value, is ranked first, portraying to be the

Table 3
Principal features chosen using Student's *t*-test.

Selected Features	Normal		Schizophrenia			
	Mean	SD	Mean	SD	p-Value	t-Value
hc	1.2100	0.1719	0.9780	0.2633	3.09E-59	17.2186
bs-1	381.4749	72.9306	457.9451	99.7012	6.37E-44	14.5133
bs-2	50.1034	7.6933	57.2959	9.9305	2.02E-38	13.4571
kc	5.6173	0.2829	5.8803	0.3643	3.71E-38	13.4050
hm	0.3900	0.0836	0.5321	0.2343	1.2E-36	13.1039
pe	1.6680	0.0712	1.6026	0.0958	2.09E-35	12.8527
re	−15.4577	0.8133	−16.0556	0.9915	9.33E-27	10.9856
bs-3	664.9682	121.2538	757.4083	157.32	1.54E-26	10.9357
lx	3.2315	0.7140	3.6562	0.9278	4.83E-17	8.5240
bs-4	8834452	8481768	13995401	16189034	9.32E-11	6.5392
bs-5	0.2533	0.0699	0.2789	0.0843	4.69E-08	5.5000
bs-6	0.5727	0.0831	0.6001	0.0923	2.02E-07	5.2295
k-s	0.0405	0.0363	0.0303	0.0383	5.31E-06	4.5740
bs-7	0.1567	0.0541	0.1726	0.0654	1.13E-05	4.4110

most significant feature. Entropy, with the highest p-value, is ranked fourteenth, portraying to be the worst feature, for the classification of EEG signals. Analysing the p values ($p < 0.05$) from Table 3, it is clear that the 14 features are highly discriminatory. Hence the features correlate to the classification. From Fig. 3, it is evident that the recurrence plot is unique for each class. While the pattern is inconsistent and random in normal signals, it is more repeated and consistent in the sz signals.

The boxplot in Fig. 4 represents the 14 best features extracted from EEG signals for classification. It demonstrates that generally most of the entropy features are of higher values for normal, compared to sz classes, due to more neural activities in the normal classes as compared to sz classes. These features are then considered for training and testing of the classifier system, which can help to categorize EEGs into normal versus sz classes. Table 4 presents the summarised results of the different classifiers used. It is evident that when the feature size is 2, a classification accuracy of 78.28% was obtained for EEG classification using the LD classifier. Hence, it can be noted from this table that the highest accuracy of 92.91% was yielded by the SVM(RBF) classifier with 12 features, as compared to the other classifiers considered in this research work. The accuracy of the SVM(RBF) classifier for varying number of features is highlighted in Fig. 5.

The LD classifier offers a relatively poor result since it was trained and tested with only two dominant features. However, compared to other techniques, the LD classifier offers a result with lesser computational time. The SVM3 is ranked at second position, requiring only 12 dominant features. The DT and SVM require 13 significant features, and other approaches require a feature subset greater than 13. From the above results it can be observed that the average performance obtained with the SVM (SVM-RBF) is superior compared to other approaches, and the SVM, SVM3, and SVM2 are ranked at position one, two and three, respectively. From the above results, it can be considered that the proposed automated tool with SVM classifier is exceptional for the classification of normal and sz EEG signals.

Comparing the other studies in Table 1, it is notable that the researchers have explored other analysis techniques instead of a classification system. Johannesen et al. [27] developed a classification system but the accuracies yielded are lower than that of our study. V. Jahmunah et al. [51] used a deep learning technique for the classifiaction, achieving a very high accuracy. However, deep learning models are computationally expensive and require a longer time to be developed as compared to machine learning techniques. Hence, our proposed system is competent to be used as a diagnostic tool for the detection of sz.

Our proposed ADT employs a sequence of procedures to examine the multi-channel EEG signals ranging from pre-processing to validation, and this motivates future work. Furthermore, the final classification accuracy is dependent on the performance of intermediate procedures, including pre-processing, feature extraction, and feature selection. In our future work, a suitable deep-learning procedure based on a deep Convolutional Neural Network (CNN) architecture shall be

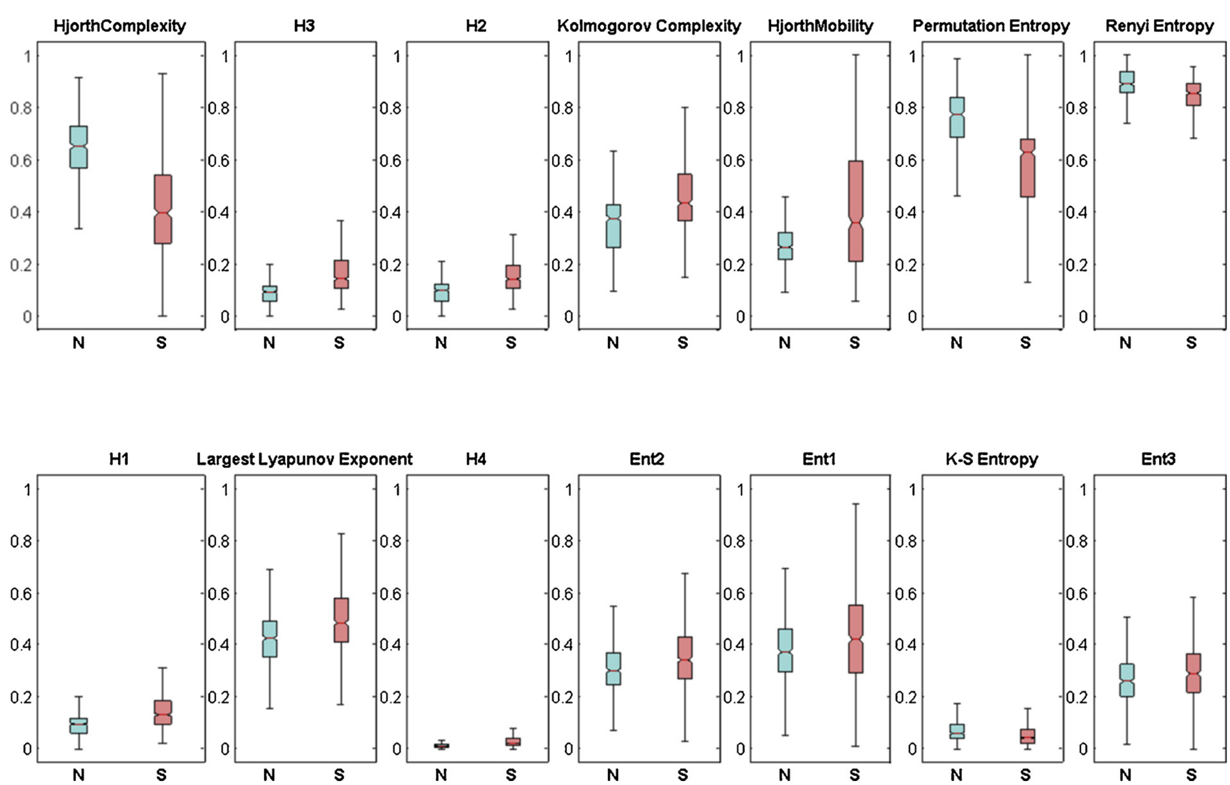

Fig. 4. Performance of selected features on normal/schizophrenia EEG signals.

Table 4
Best results achieved from different classifiers used.

Classifier	No of Features	TP	TN	FP	FN	Accuracy	PPV	Sensitivity	Specificity
SVM(RBF)	**12**	**585**	**476**	**40**	**41**	**0.929072**	**0.936**	**0.934505**	**0.922481**
SNM(Polynomial3)	12	564	488	28	62	0.921191	0.952703	0.900958	0.945736
SVM(Polynomial2)	13	565	486	30	61	0.920315	0.94958	0.902556	0.94186
KNN	6	568	464	52	58	0.903678	0.916129	0.907348	0.899225
DT	12	561	448	68	65	0.883538	0.891892	0.896166	0.868217
PNN	14	535	451	65	91	0.863398	0.891667	0.854633	0.874031
SVM(Polynomial1)	14	483	437	79	143	0.805604	0.859431	0.771565	0.846899
LD	2	493	401	115	133	0.782837	0.810855	0.78754	0.777132

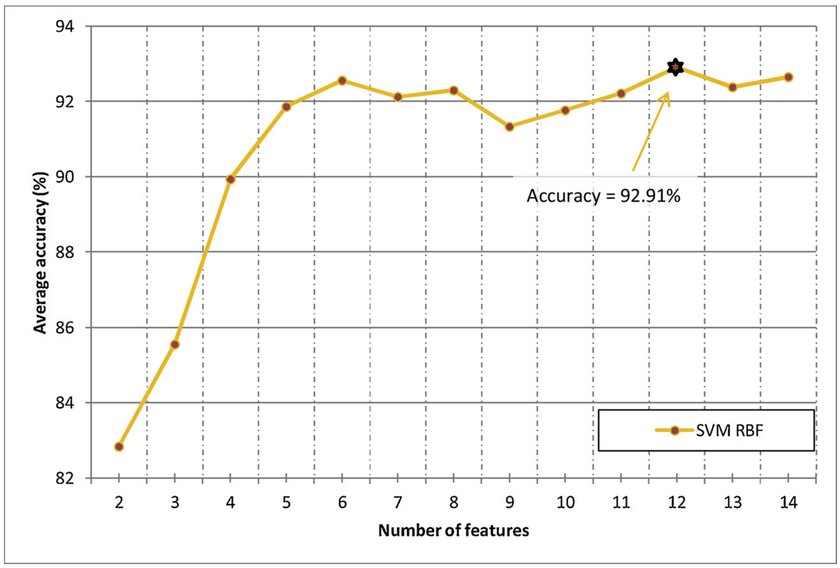

Fig. 5. Classification accuracy of SVM(RBF) with different number of features.

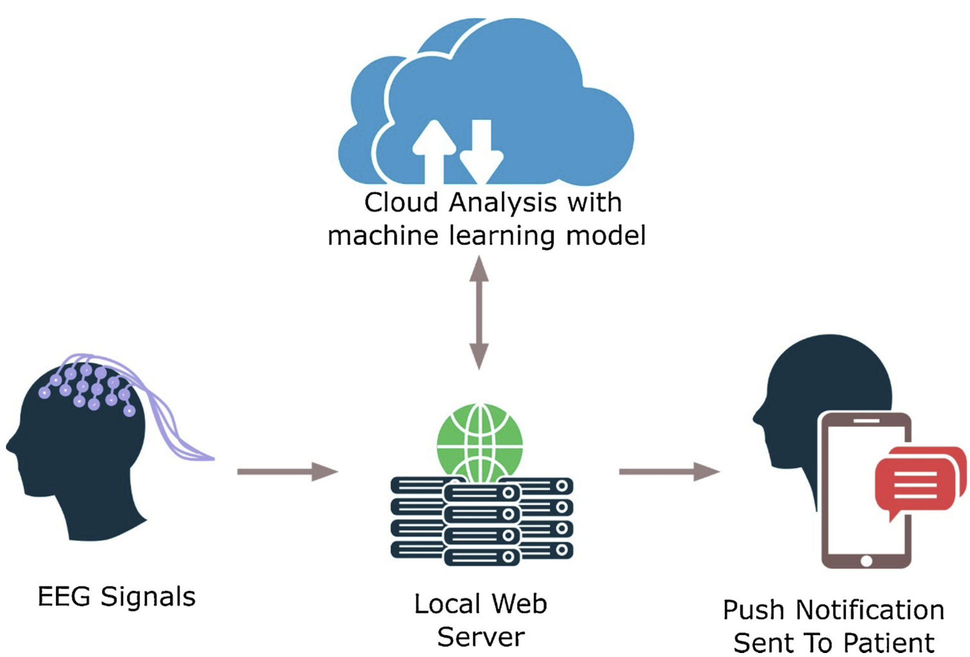

Fig. 6. Illustration of the proposed cloud model.

implemented to examine the EEG dataset. Deep learning is advantageous as the features are extracted and classified automatically by the model, unlike the conventional machine learning techniques. Additionally, these models have sizeable learning capacity, enabling higher level features to be studied through learning of data from large datasets, as compared to the traditional machine learning techniques. Hence, the classification accuracy may be higher.

Moreover, assessment of the EEG time series could also be examined using machine-learning and deep-learning techniques. The developed model can be placed in the cloud to diagnose the sz class quickly and accurately. The test EEG signals would first be sent to the local web server of the hospital. Thereupon, the signals would be ported to the cloud, where our trained sz detection machine learning model is placed. This model will automatically detect the unknown class and send it back to the hospital server. The neurologist can confirm the class manually, and release the result to the patient's mobile device. Hence, the patient can immediately take medication or rush to the hospital for the treatment, as needed. Fig. 6 depicts the proposed cloud model.

5. Conclusion

The proposed ADT involves the extraction of nonlinear features from signals, *t*-test based feature selection, and performance validation of the different classifiers reconnoitered. The SVM(RBF) classifier yielded the highest accuracy of 92.91% as compared to the other classifiers employed in this work. It achieved the best accuracy with 12 features, and portrays as the best classifier. This confirms that the proposed technique is expedient in the classification of normal versus sz cases. Although the proposed method is promising, extracting the features and performing feature selection manually can be cumbersome. To address this, in the near furture we intend to employ the CNN deep learning model coupled with the cloud machine for the efficacious diagnosis of sz.

Declaration of Competing Interest

The authors declare that they have no conflicts of interest.

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