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RESEARCH ARTICLE

AUTOMATED PSYCHIATRIC DATA ANALYSIS from SINGLE CHANNEL EEG with SIGNAL PROCESSING and ARTIFICIAL INTELLIGENCE METHODS

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ABSTRACT

Artificial Intelligence (AI) methods have been generally used in neuroimaging data to identify patients with psychiatric problems/disorders. Schizophrenia (SZ) is generally defined as a mental problem that affects the thinking ability and memory. Manual assessment of SZ participants is sometimes difficult and susceptible to diagnostic mistakes. Thus, we achieved a Computer Aided Diagnosis (CAD) algorithm to analyze and interpretate SZ patients successfully using single channel measurement Electroencephalogram (EEG) signals with Signal Processing and Artificial Intelligence methods. First, the EEG signals of participants were pre-processed (signal enhancement, filtering, noise removal), Then, signals were disseminated into windowing/segmentation process. Then, the EEG signals are separated with wavelet decomposition via seven sub-bands. Next, the feature extraction process was achieved and specific feature parameters were obtained by summing the numerical values of the processed signals. Then, Feature ranking process was achieved to identify the obtained features of the normal and schizophrenia groups. After ranking process, features are fed to AI (SVM), We have obtained the highest accuracy of 99.31% using SVM with five fold and take off one cross validations.

Keywords: *Schizophrenia (SZ), Single Channel EEG, Computer Aided Diagnosis (CAD), Artificial Intelligence, Feature Extraction*

1. INTRODUCTION

The brain's main function is controlling the work of the entire body and the problems might affect normal/common activities. The common thing of the mental disorder is that any mental disease may impact the human body, also thinking and other important functions. The schizophrenia (SZ) could be a complex, inveterate mental wellbeing clutter characterized by a extend of indications counting daydreams, mental trips, disorganized discourse or conduct, and impeded cognitive capacities. Yet, the exact and ultimate treatment is not available. Objectives within the treatment of schizophrenia incorporate soothing side effects, avoiding backslide, and expanding versatile working so that the persistent can be reintegrated into society. The early and successful location of SZ is fundamental since it influences the quality of living.

In psychiatry, mental diseases are investigated using physiological signals and some questionnaire methods. Nowadays, electroencephalogram (EEG) signals are chosen as a common way to study brain-related disorders. Indeed, these signals are easy for multi-channel acquisition and also more economical. The radiological imaging techniques (MRI and CT) are costly and take more time for obtaining the result. With using these EEG signals, different types of disorders can be easily interpretated. One type of the disease is commonly Parkinson's disease [1], sleep disorders [2, 3], dementia, Alzheimer's disease and other mental disorders [4-8].

Some insights can be provided by recent studies about computer based SZ classification using EEG signals. Kim et al. (2015) worked on EEG signals according to the 10-20 international positioning standard [9]. They gotten completely five recurrence groups and they computed the control parameter with utilizing Fast Fourier Transform (FFT), The accuracy was obtained as approximately 62%. Indeed, Dvey-Aharon studied about EEG signals with using Stockwell approach and Time-frequency transformation was applied to these signals [10]. For five electrodes, the accuracy was obtained as approximately 92%. Santos-Mayo et al. (2016) utilized brain vision equipments for obtaining the single-channel EEG signals, then they used EEG-LAB interface for pre-processing [11]. Totally 16 features were obtained for each electrode and these were classified with Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM), Finally, the accuracy was obtained as 93.42% for MLP and 92.23% for SVM classification. Also, Ibanez-Molina et al. (2018) investigated a study which was about the EEG-based SZ assessments [12]. The resting state EEGs were chosen and used and they were obtained via specific amplifiers. The analyzing process was achieved with using a sliding window over the whole EEG recording. Next, Lempel-Ziv complexity (LZC) was computed from the signal [13]. According to 80 EEG segments the final multiscore LZC score was obtained. Moreover, Oh et al. (2019) observed a system with Deep Learning for classification EEG signals of SZ patients [14]. They used Convolutional Neural Network (CNN) with specific parameters and according to ten-fold cross validation the accuracy was obtained as approximately 98%. Vicnesh et al. (2019) studied on a CAD system for classifying two groups of patients from EEG segments [15]. The accuracy was obtained as 93% with using SVM classifier with 12 features. Sharma et al. (2021) studied on automated detection of SZ from EEG segments with using KNN classifier [16]. They were reported the accuracy as 99.21% from a single channel EEG.

Our proposed system was given in Figure 1. The EEG recordings were pre-processed (signal enhancement, filtering/noise removal), Then, signals were disseminated into windowing/segmentation into 25 epochs according to the World Health Organization (WHO) sleep recording analysis criteria. Then, the EEG signals are disseminated into the wavelet decomposition via seven sub-bands. Next, the feature extraction process was achieved and some feature parameters (Linear features as EEG asymmetry, amplitude, frequency, I_1 norm value; nonlinear features as Energy, Spectral Energy Density, Shannon Entropy, Spectral Entropy, Correlation, Fractal Dimension (FD), Higher Order Spectra (HOS), Hurst's Exponent, Detrented Fluctuation Analysis (DFA)) were obtained by summing the numerical values of the sub-bands. For Feature Extraction process, only signal's I_1 norm value was computed from itself and 6 subbands of Cz channel. The other features were computed from only the processed Cz-channel. At that point, Feature ranking was accomplished to distinguish and rank the centrality of the extricated features. The profoundly positioned features are encouraged to AI (SVM), The five-fold cross validation strategy is for the most part utilized to prepare and select the finest classifier, which accomplishes tall classification accuracy with least number of highlights. The most highlights of proposed think about are as takes after.

1. We have accomplished a single-channel EEG based CAD framework while a few of the existing considers given in Table 6 are utilized numerous channels [15, 16, 17]. Therefore, our sytem is simple and easy to use for patients.

2. In this study, we used a lot of important features for discriminating the EEG recordings. This study can be explained as a complex but according to the usage, the system is very portable.

3. In the proposed study, we have used some novel features for signals in detail such as Linear features as EEG asymmetry, amplitude, frequency, I_1 norm value; nonlinear features as Energy, Spectral Energy Density, Shannon Entropy, Spectral Entropy, Correlation, Fractal Dimension (FD), Higher Order Spectra (HOS), Hurst's Exponent, Detrented Fluctuation Analysis (DFA), These salient features were fed into AI.

4. Simulation results reveals that the proposed method has important AUC values and the accuracy of 99.31% for SVM using only the Cz-EEG channel.

5. In the proposed work, we have created a novel ideal multiple-band orthogonal channel bank, so channels are ideally gotten and localized within the frequency space.

6. To ensure the system's performance stability and avoiding possible overfitting problems, we used 5-fold cross validation and hold out validation.

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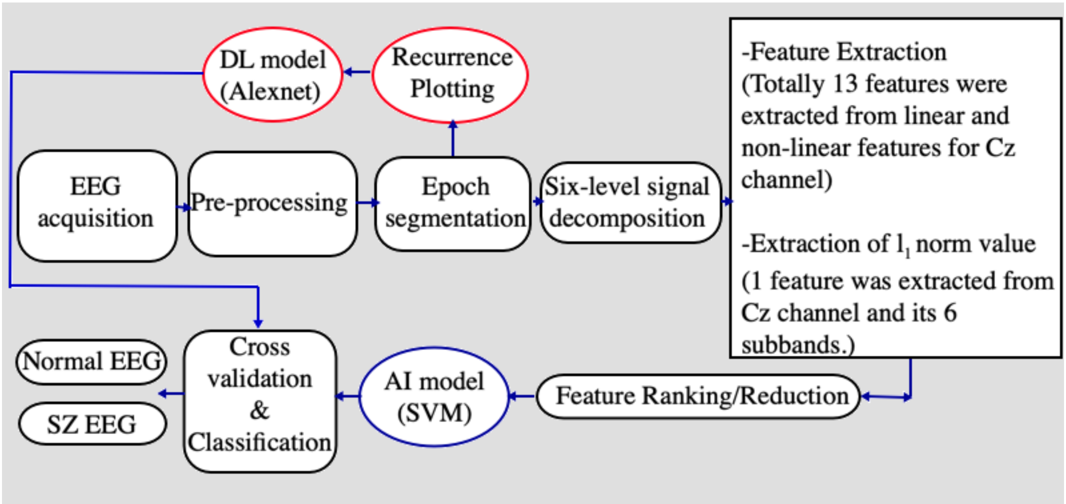

Figure 1. Proposed system flow diagram (and future implementation with Deep Learning-AlexNet model),

2. MATERIAL and METHODS

2.1. Data Set

36 SZ patients (18 females-18 males) and 36 normal members were utilized with a normal age of 35.3 ± 4.1 and 33.9 ± 3, separately. Open access information was obtained from the Research Facility for Neurophysiology Interfacing from Moscow State University-Faculty of Science. The EEG signals were recorded on a multichannel with a testing frequency of 128 Hz. All electrodes were utilized as T4, T6, Fp2, F8, Fp1, F7, F4, Fz, T3, T5, O1, O2, C4, P4, P3, F3, C3, Cz and Pz. The inspecting frequency of EEG signals is chosen 128 Hz for digitizing the EEG recordings. The duration of each epoch is 60s; hence, each epoch contains 7680 samples. Figure 2 and 3 shows the EEG signal from Cz-channel of two groups of patient. Table 1 moreover incorporates the points of interest of the data-set. 16-channel EEG signals comparing to the normal and SZ classes are given in Figure 4 and 5, individually.

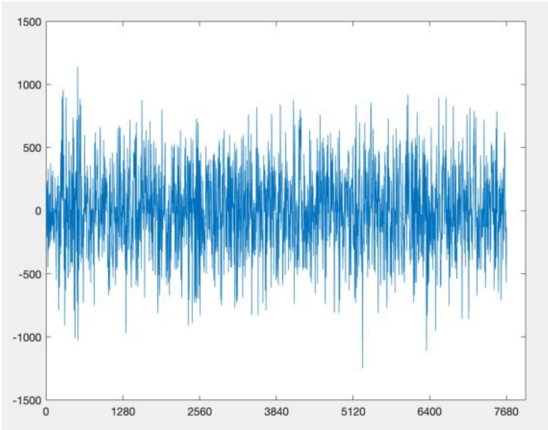

Figure 2. Random EEG signal of acquired from Cz-channel of normal participant.

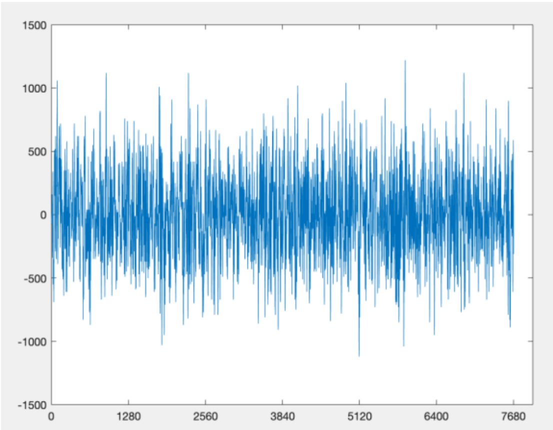

Figure 3. Random EEG signal of acquired from Cz-channel of SZ participant.

Table 1. Details of used dataset.

Type	**Number of Participants**	**Average age value of male and female**
Normal	36(18M+18F)	35.3 ± 4.1, 33.9 ± 3.1
SZ	36(18M+18F)	35.3 ± 4.1, 33.9 ± 3.1

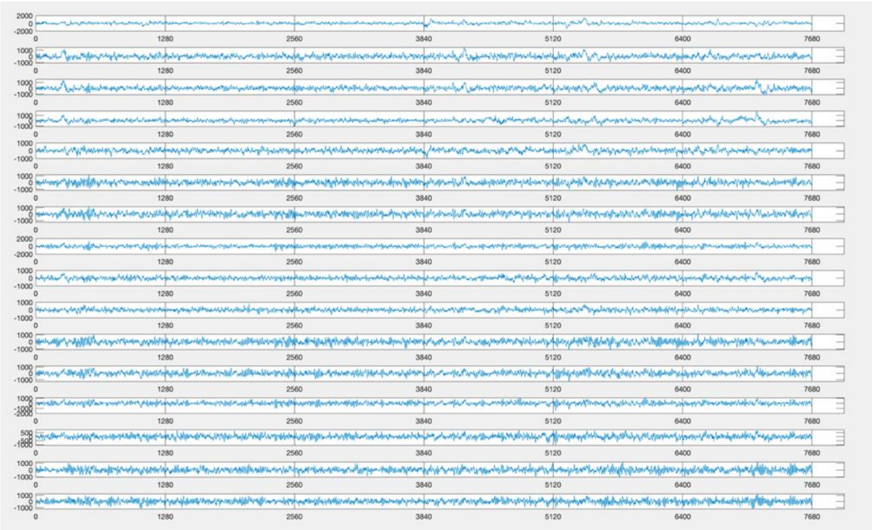

Figure 4. EEG subsignals of a normal participant. Y-axis represents F7, F3, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2, respectively.

X-axis represents number of samples at sampling frequency 128 Hz.

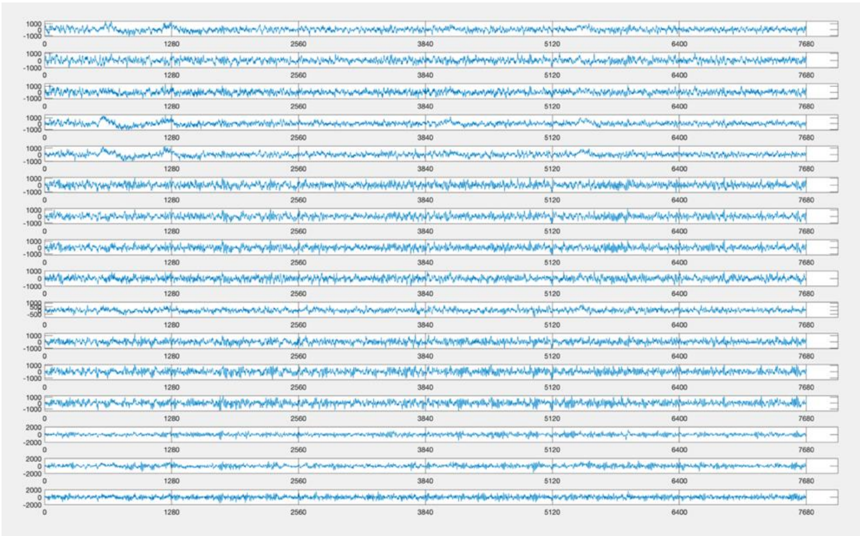

Figure 5. EEG subsignals of a SZ participant. X-axis represents number of samples at sampling frequency 128 Hz.

2.2. Proposed Method

For this study, EEG signals were sampled at 128 Hz. Firstly, these signals were pre-processed by filtering with sixth-order Butterworth filter and signal enhancement methods. The specific details are given in Table 1.

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2.2.1. Pre-processing (optimal filter design and filtering), epoch segmentation and six-level-signal decomposition

Because of being time-varying and non-stationary, the Fourier Transform (FT) can sometimes not be effective for the analysis of signals in detail [18]. Then, this problem can be eliminated by using Fast Fourier Transform (FFT) by analyzing the signal into windows and then the whole information is gathered from these slices. It is important that for FFT, specific details of the signals have to be obtained in both frequency spaces. Wavelet is called the significant device that gives the data around almost a signal in both spaces [19, 20]. The wavelet primarily disseminates the signal into little windows in arrange that the specified data can be gotten from scaling and moving forms. For this ponder, for signal investigation, a two-orthogonal-channel was in a general sense utilized. For getting ideal comes about, the mean-squared-frequency-spread of the channels was utilized for planning the limited orthogonal wavelet banks. The ideal channels utilized in this think about have ideal and least recurrence spread and the effective number of zero moments. Without a doubt, frequency localization can be communicated as an imperative quality in planning ideal channels. Moreover, cut-off frequencies regarding to the stop passbands do not be required and instead of this situation, the RMS bandwidth can be considered for this issue because this bandwidth is related to the entire spectrum of the signal [21]. The whole filter coefficients of low pass filter for using in wavelet decomposition are given in Table 2, respectively.

Table 2. Coefficients of optimal LPF filter.

Number	Coefficient value
1	0.1225
2	0.4996
3	0.7622
4	0.3252
5	-0.2126
6	-0.1197
7	0.0997
8	0.0248
9	-0.0295
10	0.00077
11	0.00455
12	-0.0015

2.2.2. Feature extraction

In this section, some specific parameters called as features were computed from EEG signals. For this phase, totally 13 features were extracted from linear and non-linear features for Cz channel of the EEG signals. Indeed, 1 extra feature as l_1 norm values was extracted from Cz channel and its 6 sub-bands. In Figure 7, sample bispectrum magnitude plots of the sample EEG signals given in Figure 2 for normal and Figure 3 for SZ patient.

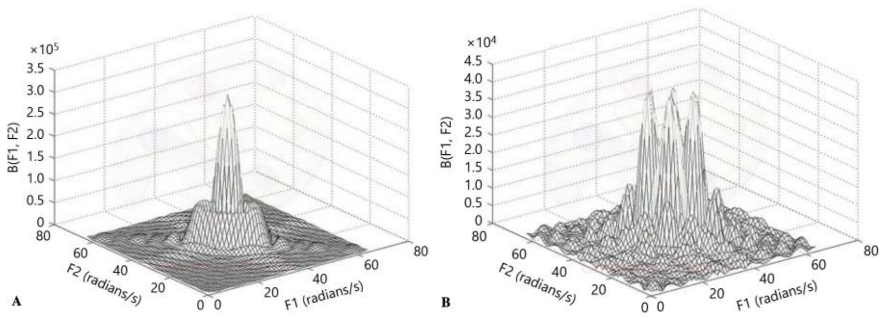

Figure7. Sample bispectrum magnitude plots of Figure 2 (normal participant) and Figure 3. (SZ patient),

Non-linear features obtained from signals;

- Energy [22]:

In signal processing, the energy E of s continuous time signal x(t) can be expressed in Eq. (2);

$$E = \int_{-\infty}^{\infty} |X(t)|^2 dt \qquad (1)$$

Indeed, the energy E of the discrete time signal x$[n]$ can be expressed in Eq. (3);

$$E = \sum_{-\infty}^{\infty} |x[n]|^2 \qquad (2)$$

- Spectral Energy Density [23]:

The spectral energy density of the signal X(t) is given in Eq. (4);

$$E(f) = |X(f)|^2 \qquad (3)$$

Where X(f) is the Fourier Transform of X(t),

- Shannon Entropy [24]:

Information entropy S is defined as:

$$S_{en} = - \sum_{i=!}^{N} p(xi) log_a^{p(xi)} \quad (a>1) \qquad (4)$$

where p(xi) are probabilities of acknowledgment by the arbitrary variable x values xi. Shannon entropy is clarified by a degree of vulnerability related with the event of the result. At long last, a better esteem of the entropy gives a more questionable result and it is said that it is more troublesome to anticipate.

- Spectral Entropy [25]:

Spectral entropy primarily employments the Fourier change strategy and the power spectral density (PSD) can be gotten. The PSD speaks to the dispersion of control as a work of recurrence. So, normalization of P(f) yields a likelihood thickness work. Utilizing the definition of Shannon's entropy, spectral entropy can be characterized as:

$$\mathrm{Sp_{en}} = \sum_{i=flow}^{fhigh} p(i)\log(pi) \quad (5)$$

Spectral entropy is usually normalized $\mathrm{Sp_{en}}/\log N_f$, where N_f is the number of frequency components in the range $[f_{low}, f_{high}]$.

○ Correlation [26]:
First, we have to express defining a convolution between two continuous time signals x(t) and a(t) is given by;

$$\mathrm{y(t)} = \int_{-\infty}^{\infty} x(T)a(t-T)dT \quad (6)$$

Then, we have to express defining a convolution between two discrete time signals x[n] and a[n] is given by;

$$\mathrm{y[n]} = \sum_{i=-\infty}^{i=\infty} x[i]a[n-i] \quad (7)$$

The correlation between the same two signals given above can be expressed as;

$$c(t) = x(t) * a(t) = x(t) \otimes h(-t) \quad (8)$$

Where $\otimes$ operand i represents the convolution operation. For discrete time signals, the correlation between the same two signals can be expressed as

$$\mathrm{c[n]} = \sum_{i=-\infty}^{i=\infty} x[i]a[i-n] \quad (9)$$

○ Fractal Dimension [27]:
Fractal Measurements (FD) are one of the prevalent measures utilized for characterizing signals. They have been utilized as complexity measures of signals in different areas counting discourse and biomedical applications. The fractal measurement has been calculated by utilizing the DWT and this will be gotten by the taking after condition:

$$\mathrm{level_{max}} = \log(n) / \log(2) \quad (10)$$

where n is the number of focuses of each considered window/signal [28]. After the DWT is connected, two vectors, x[n] and y[n] were produced [28, 29]. Once the vectors are decided, the fractal measurement can be calculated concurring to Eq. (12):

$$D = 2 - \left|\frac{\beta-1}{2}\right| \quad (11)$$

where, β is the point of the normal line given by the vectors x[.] (length of each leaf) and y[.] (energy of each leaf), by implies of the least squares method [28, 29].

○ Higher Order Spectra (HOS) [30]:
HOS comprises of higher-order moment spectra, which is characterized for deterministic signals, and cumulant spectra. In common there are three inspirations behind the utilize of

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HOS investigation in signal preparing: First, to smother Gaussian noise and fluctuation within the range of location and parameter estimation issues. Second, to reproduce the stage and the size reaction of signals/systems. Third, to detect and characterize nonlinearities within the information.

$$C(w1,w2) = \sum_{r1=-L}^{L} \sum_{r2=-L}^{L} C(T1,T2)\, e^{-j(w1T1+w2T2)} W(T1,T2<\theta). \tag{12}$$

where L < M -1, and W(Tl, T2) is a two dimensional window, used to smooth out edge effects.

○ Hurst's Exponent [31]:
The Hurst exponent is alluded to as the "file of reliance" or "record of long-range reliance". It explores the relative inclination of a time arrangement. A esteem H within the run 0.5–1 shows a time arrangement with long-term positive autocorrelation. This in differentiate to the ordinarily control law rot for the 0.5 < H < 1 and < H < 0.5 cases. The Hurst exponent, H, is characterized in terms of a time arrangement as follows;

$$C_n^H = E(R(n)/S(n)) \quad (n \rightarrow \infty), \tag{13}$$

where; R(n) is the run of the primary n total deviations from the cruel, S(n) is the series (whole) of the primary n standard deviations, E|x| is the anticipated esteem, n is the time span of the perception (number of data points in a time arrangement), C could be a constant.

○ Detrented Fluctuation Analysis [32]:
For DFA, it is useful for analyzing time series that appear to be long-memory processes or 1/f noise.
It isn't always the case that the scaling exponents are independent of the scale of the system. In the case depends on the power extracted from;

$$F_q(n) = \sqrt[q]{\left(\frac{1}{N}\sum_{t=1}^{N}(X_t - Y_t)^q\right.} \tag{14}$$

Linear features obtained from signals;

○ Asymmetry [33]:
This feature regards to measure symmetry by taking any suitable norm on the signals. For example the symmetry of f(x) can be measured as;

$$s[f] = \|f+\|/(\|f+\| + \|f-\|) \tag{15}$$

$$\|f\| = \sqrt{\int_R f(x)^2 dx} \tag{16}$$

which ranges from 0 (fully asymmetric) to 1 (fully symmetric),

○ Amplitude:
This feature regards to the peak-to-peak value of the signal. This value is obtained from the signals and used in Feature Extraction part.

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- Frequency:

This feature regards to the frequency value (f=1/period) of the signal. This value is obtained from the signals and used in Feature Extraction part.

- l_1 Norm Value [34]:

The l1 standard highlight of subbands has been computed in this work. The l1 standard can be basically calculated as;

$$l_1(x) = \sum_{n \in Z} |X(n)| \tag{17}$$

where n is the index of the sequence x(n) and Z denotes the set of integers.

2.2.3. Feature ranking/reduction:

Feature/Variable Ranking is the method of requesting the features by the esteem of a few scoring work, which ordinarily measures feature-relevance. A straightforward strategy for highlight determination using variable ranking is to choose the k-highest positioned highlights concurring to signal.

2.2.4. Classification with aı model via cross validation [35]:

All these calculated numerical feature vectors were first fed into Support Vector Machine (SVM), which is a classical Artificial Intelligence (AI) method, and the system learned it. Classification can be mainly defined as distinguishing and identifying situations or objects with similar characteristics from those with other different characteristics.

2.2.4.1. Support vector machines (svms)

SVM is fundementally used as an effective AI method for classification processes. The SVM algorithm allows to work on small and large data sets in order to extract important information from data sets [36]. The main purpose in the SVM algorithm is to create a learning task with a given finite number of training data. The SVM learning method is achieved with an optimally separated hyperplane that maximizes the margin (the shortest distance to the data point.

2.2.5. Training, testing and validation

In this think about, the information set utilized was obtained from 16 channels. For each EEG age, seven l1 standard highlights and completely 10 direct and nonlinear highlights were computed. Firstly, each channel have tried independently and we took all highlights 16 channel EEG signal for classification utilizing five fold cross-validation. The channel (Cz) was utilized with take off one validation and hold out endorsement. In TOCV, 35 subjects out of 36 were utilized to plan the illustrate, and the remaining one utilized for testing the illustrate. We as well performed hold-out endorsement for the Cz channel that gave the foremost great execution utilizing the five-fold CV [35, 36]. In this technique, from 10% to 50% hold-outs are utilized, respectively.

3. RESULTS

We arranged the proposed CAD utilizing Macbook Pro 13 inch 16.0 GB and 64-bit working system and MATLAB R2019a adaptation was utilized. The highlight extraction time has been generally 3 seconds. Highlights were situated utilizing t-test and t-test was utilized to evaluate the estimations of the assortment. The t-value illustrates whether the two classes were assorted or not. The typical time taken for planning and testing is 5.75 p. The classification was accomplished with SVM (with Feature

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Extraction) for the Cz channel utilizing the five-fold CV is given in Table 3. Figure 8 appears recipient working characteristic (ROC) comparing to the Cz channel when the classification is performed utilizing all highlights and SVM with five-fold CV.

Table 3. Five fold CV results.

CF	**CA**	**CS**	**CSF**	**F1 value**
With SVM	98.4%	99.53%	99.10%	99.18%

CF:classifier, CA: classification accuracy, CS: classification sensitivity, CSF: classification specificity

The classification accuracy of the adjusted subset has been found to be 98.4% for SVM.

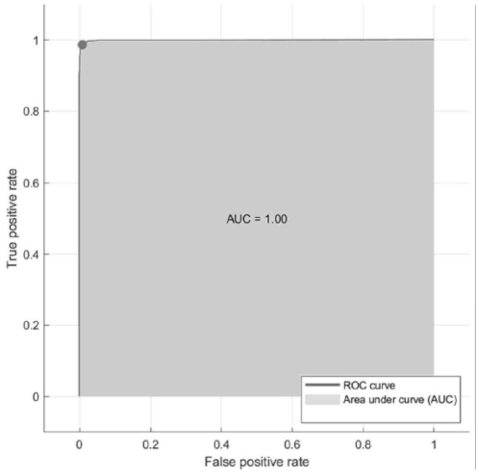

Figure 8. ROC analysis results using SVM with five fold CV.

In arrange to guarantee over-fitting, we utilized TOCV for the classification models utilizing Cz channel. For this demonstrate, the accuracy of 99.31% and F1-score of 99.52% accomplished for SVM with TOCV. In fact, the accuracy of 99.61 with TOCV. The disarray framework and classification come about for holdout approval with SVM classifier were appeared in Tables 4 and 5, separately. The leading classification accuracy is 99.82% for 30% holdout validation.

Table 4. Confusion matrix using Cz channel.

Holdout value (%)	**True negative**	**False positive**	**False negative**	**True positive**
10	51	1	0	62
20	102	3	0	124
30	156	0	2	187
40	205	2	2	246
50	254	5	3	311

Table 5. Results obtained using Cz channel.

Holdout value (%)	Accuracy	Sensitivity	Specificity	F1 value
10	99.22	99.98	98.34	99.05
20	98.88	99.12	98.31	98.64
30	99.82	99.45	99.37	99.45
40	98.92	98.65	99.20	98.89
50	98.62	98.86	98.46	98.60

4. DISCUSSION

Filtering was achieved with the optimal filter bank for wavelet decomposition. After filtering with max seven decomposition levels, l_1 norm value was computed for each wavelet and also linear and non-linear features were computed for the whole EEG processed signal epochs. Indeed, it was found that the features correspond to the sixth level gave the best performance metrics to us. After classification with the AI model using five-fold CV, we obtained the best accuracies of 99.31% and 99.68% for Cz-channel of EEG signals, respectively. Table 6 gives detailed information about the studies with distinguishing normal and SZ EEg signals.

Table 6. Comparison of our results for SZ detection in literatüre.

Study	Method	Number of participants	Dataset	CA (%)	Used electrodes
Johannesen et al. (2016)	SVM	Normal:12 Abnormal:40	VACHS, Yale	Model 1:84 Model 2:87	Cz, Fz, Oz
Santos-Mayo et al. (2016)	MIFS or DISR	Normal:31 Abnormal:16	Dep. of EEE University of Vallodolid	MLP: 93.42 SVM: 92.23	C3, C4, Cz, F3, F4, F7, F8, Fp1, Fp2, Fz, O1, O2, P3, P4, Pz, T5, T6
Oh et al. (2019)	11-layered CNN	Normal:14 Abnormal:14	Inst. of Neurology, Warsaw, Poland	81.26	Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2
Vicnesh et al. (2019)	SVM, KNN, LD, PNN, DT	Normal:14 Abnormal:14	Inst. of Neurology, Warsaw, Poland	92.91	Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2

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Sharma et al. (2021)	l_1 norm, ES-KNN	Normal:14 Abnormal:14	Inst. of Neurology, Warsaw, Poland	97.2	Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2
Our proposed method	l_1 norm, linear and nonlinear features, SVM	Normal:36 Abnormal:36	Laboratory for Neurophysiology and Neuro-computer Interfaces from Moscow State University	SVM:99.31	F7, F3, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2

According to the table given above, our proposed system can efficiently distinguish normal and SZ classes from EEG signal epochs. Moreover, with using AI model of SVM, advanced and optimal features were chosen and used optimally in the Feature Extraction part and classification was achieved successfully. Thus, according to the table, our system has better performance results than the other related studies from literature.
Main advantages of our proposed method are:

1. Obtained successful and high accuricies of 99.31 for SVM using only Cz channel of EEG signals with LOCV and five-fold cross validation. Furthermore, the system is more accurate and efficient.

2. Obtained high classification performance results are also important.

3. With using complex and detailed features, features were calculated and also one feature was calculated from seven subbands of the signal via wavelet decomposition. Finally, Feature extraction was achieved for AI model successfully and robust.

4. Developed and more efficient wavelet based decomposition system (filter bank)

In near future, the system can be improved and will be used in the pre-diagnosis CAD systems for detecting some important EEG, Polisomnograpghy (PSG) based disorders, so life will become easier via these CAD systems.

5. CONCLUSION

Methods that help and facilitate the diagnosis of mental illnesses are attracting attention. In this study, a unique methodology for successful detection of schizophrenia using specific complex features via Feature Extraction from single case/channel Cz EEG signals. Indeed, for this study, optimized orthogonal wavelet filters are developed for accurate detection of schizophrenia. Then, 13 specific features were calculated from signals and it is important that one of the features was calculated from seven subbands of EEG signals and the other features were calculated from whole processed EEG signals of participants. In this work, for AI, SVM model was used and highest classification results were obtained. Also, we achieved detailed comparable analysis and classification with EEG signals in this study with using TOCV and five-fold CV. The methods are mainly less expensive than the existing methods. With using our proposed methods, we obtained important higher classification performance results. The proposed model can be developed to different areas in Biomedical Engineering for online monitoring of schizophrenia. In the future, the main aim will be testing this system with some other diverse and big databases with different EEG based mental disorders.

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