EEG Signal based Schizophrenia Recognition by using VMD Rose Spiral Curve Butterfly Optimization and Machine Learning

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***Abstract*—Schizophrenia is a mental illness that can negatively impact a patient's mental abilities, emotional propensities, and the standard of their private and social lives. Processing EEG data has evolved into a useful tool for tracking and identifying psychological brain states. In this framework, this paper focus on developing an automated approach for recognizing schizophrenia using non-invasive EEG signals. The EEG signals are segmented and onward decomposed by using the Variational Mode Decomposition (VMD). Each mode is termed a variational mode function (VMF). Onward, features from each intended VMF are mined based on a Rose Spiral Curve (RSC). The mined features are concatenated to present an instance. Afterward, the most pertinent features are selected using the Butterfly Optimization Algorithm (BOA). The selected feature set is conveyed to the classification module. Two classification approaches are applied in this study namely, the k-nearest neighbor (k-NN) and Random Forest (RF). The applicability is tested by using a publicly available EEG schizophrenia dataset. The highest accuracy of 89.0 % is secured for the case of RF.**

Index Terms*—Electroencephalogram, *Segmentation, Variational Mode decomposition, Metaheuristic Optimization, Features Extraction, Machine Learning, Schizophrenia, Classification.

I. Introduction

Schizophrenia (SZ) is a serious brain condition that affects a person's thinking, memory, comprehension, speech, and behavioral traits [1]. When a person's quality of life is damaged due to their chronic mental disease, it affects their career, marriage, and lifestyle, and 20–40% of them make at least one attempt at suicide [2]. According to the World Health Organization (WHO), this mental illness affects 20 million individuals globally [1]. However, the WHO has also said that SZ is treatable, and that an accurate and prompt prognosis is beneficial for better treatment and the patient's recovery.

The SZ usually starts to create problems at a young age, and the harm it does gets worse with time. Initiating long-term therapy that might aid in lowering brain deformations requires an early diagnosis and a prompt prognosis.

Interviews and behavioral indicators including hallucinations, functional deterioration, and disordered speech are typically used to diagnose SZ. This laborious and drawn-out assessment needs a licensed psychiatrist and takes time. Therefore, to assist doctors in beginning medical therapy as soon as possible, it is vital to design an automated model to diagnose patients.

To understand brain activity and diagnose mental diseases including depression [3], [4], epileptic seizures, alcoholism [5], autism [6], Parkinson's disease [7], Alzheimer's disease [8], and many others, the Electroencephalography (EEG) signals have been widely employed in research. Numerous studies have utilized EEG signals to identify SZ in the literature. Due to its cheap cost, non-intrusiveness, simplicity of setup, high temporal and spatial resolutions, and ease of use, it is regarded as the preferable approach for detection. An automated approach is required since manually filtering EEG signals is a difficult and time-consuming process.

In the literature, a lot of research has been performed on SZ diagnosis. On pre-processed EEG signals, Dvey-Aharon et al. [9] performed the Stockwell transformation [10], which transforms time-series data into temporal frequency representation from which the most important features were selected. These characteristics were utilized to train the k-Nearest Neighbor (k-NN) algorithm for patient categorization. Shim et al. [11] looked at the impact of sensor-level and source-level factors on the machine-learning-based diagnosis of SZ. Following the feature selection process, the Support Vector Machine (SVM) classifier was trained using the leave-one-out cross-validation method. Following the feature selection process, the SVM classifier was trained using the leave-one-out cross-validation method. In [12], Santos-Mayo et al. mine characteristics using a combination of time-frequency analysis and Evoked Related Potential. Then, "linear discriminant analysis," "mutual information" (MI), and "double input symmetrical relevance" were used to choose the most relevant characteristics. SVM and Multi-layer Perceptron are trained to utilize the features chosen using these three distinct techniques (MLP). By merging the characteristics provided by several electrodes, they have experimented with various electrode groupings. Relative Wavelet Energy is a method used by Aslan and Akin [13] to extract distinguishing characteristics from EEG data. These characteristics were then used to train the k-Nearest Neighbors classifier. From EEG recordings of 78 people, Thilakvathi et al. calculated the Shannon Entropy, Spectral Entropy, Higuchi's Fractal Dimension, and Kolmogorov complexity-based features in [14]. SVM and Feed-Forward Neural Networks are utilized for classification from this point forward.

There have also been attempts to utilize EEG waves to detect SZ using various deep learning architectures. Oh et al. create an 11-layered Convolutional Neural Network (CNN) model for SZ patient classification in [1].

The research of Shalbaf et al. [15] examines the impact of the frontal, parietal, central, temporal, and parietal brain areas on the identification of SZ. This method is intriguing for locating the brain area that is most important for the diagnosis of SZ. Additionally, it allows for a reduction in the number of EEG electrodes and channels that must be processed. As a result, it provides an effective solution for data management, processing, transmission, and storage. As a result of this study, we have concentrated this research on the processing of frontal EEG data for the detection of SZ.

In this paper a novel hybridization of segmentation, “Variational Mode Decomposition” (VMD), “Rose Spiral Curve” (RSC) based Modes features mining, “Butterfly Optimization Algorithm” (BOA) based feature selection and machine learning algorithms is devised for an automated identification of SZ. The intended dataset and methods are described and the results are presented and described. The limitation of this study and future works are also presented.

The remainder of this paper is structured as follows. The used materials and methods are described in Section II. Section III presents and discusses the findings, and Section IV concludes this study.

II. Materials and Methods

The suggested solution, at the block level, is displayed in Fig. 1. Different system modules are described in the following sub-sections.

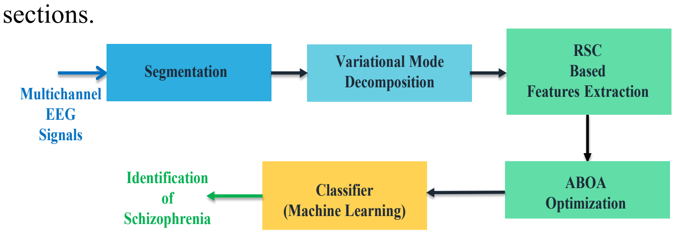

Fig. 1: The system block level diagram.

A. Dataset

The Institute of Psychiatry and Neurology in Warsaw, Poland, provides a collection of EEG signals that are used in this study. It includes data from 14 normal and 14 obsessive SZ participants. Everyone had their EEG data collected for fifteen minutes at a sampling rate of 250 Hz using the conventional 10-20 technique. During the signal capture process, all subjects had their eyes closed and were in a relaxed state. 19 electrodes are positioned on 5 distinct cortical areas to capture the EEG from normal and SZ patients.

In this study, the EEG signals captured from the frontal region comprises of channels Fp1, Fp2, F7, F3, Fz, F4, and F8 are considered.

The EEG signals are splitted into segments of 20-second length, each comprises of 5000x7 samples and it is named as an instance x. In total 1419 instances are considered, comprises of 639 control and 779 SZ instances.

B. Variational Mode Decomposition (VMD)

In the method of variational mode decomposition (VMD), the instance x is decomposed into n_k subcomponents or modes. Each mode is termed a variational mode function (VMF). Each VMF has a central frequency ω_k. The VMD generates the modes that are band-limited with compact Fourier support and has a specific sparsity property. The bandwidth of each mode is computed as follows [16]:

Step 1: By using Hilbert transform of each mode n_k, the corresponding analytic signal is derived as $\delta(t) + \frac{j}{\pi t} * \ n_k(t)$.

Step 2: To shift the frequency of each mode to the center frequency ω_k, each mode is multiplied by an exponential, which has ω_k as its center frequency. The resultant analytic signal is $[(\delta(t) + \frac{j}{\pi t}) * \ n_k(t)]e^{-j\omega_k t}$.

Step 3: To estimate the bandwidth of each mode, the squared L^2-norm of the gradient of shifted analytic signal is taken as: $||\partial(t)[(\delta(t) + \frac{j}{\pi t})] * \ n_k(t)e^{-j\omega_k t}||_2^2$

Step 4: Now, to formulate VMD as the constrained optimization problem,

$$\underbrace{\text{minimize}}_{\{n_k,\omega_k\}} [\sum_{k=1}^{n} ||\partial(t)[(\delta(t) + \frac{j}{\pi t})]] * \ n_k(t)e^{-j\omega_k t}||_2^2 \quad . \tag{1}$$

such that $\sum_{k=1}^{n} n_k = x$

Eq. (1) can be made an unconstrained optimization problem by introducing the Lagrangian multiplier λ and quadratic penalty terms. The augmented Lagrangian is defined as:

$$L(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_{k=1}^{n} ||\partial(t)[(\delta(t) + \frac{j}{\pi t})] * \ n_k(t)e^{-j\omega_k t}||_2^2 + \|x(t) - \sum_k n_k(t)\|_2^2 + \langle\lambda(t), x(t) - \sum_k n_k(t)\rangle. \quad . \tag{2}$$

The parameter α is used to balance the data fidelity constraint. To solve the original optimization problem of Eq. (2), the saddle point of the Lagrangian is determined by using the Alternate Direction Method of Multipliers (ADMM). The ADMM is an iterative method, where each mode n_k is updated in every iteration as:

$$n_k^{n+1}(w) = \frac{x(\omega) - \sum_{i\neq k} n_i(\omega) + \frac{\lambda(\omega)}{2}}{1 + 2\,\alpha\,(\omega - \omega_k)^2}. \tag{3}$$

Here, n denotes the iteration number. In each iteration, the center frequency of the mode is updated as:

$$\omega_k^{n+1} = \frac{\int_0^{\infty} \omega\, |\hat{n_k}(\omega)|^2\, d\omega}{\int_0^{\infty} |\hat{n_k}(\omega)|^2\, d\omega}. \tag{4}$$

For the in-depth derivation process of VMD, readers can refer [16]. In this study using VMD, each instance is decomposed into 11 VMFs.

C. Feature Extraction

To extract the features from each VMF, we have used phase space dimensional features. In this study, we have utilized recently reported features based on the rose spiral curve (RSC). The brief steps to compute the RSC-based features are provided as follows [17]:

First, the z-score normalized signal s is represented in two-dimensional phase space (2D-PS) as:

$$A = \cos(\pi \times s) \times \sin(s). \quad (5)$$

$$B = \sin(\pi \times s) \times \cos(s). \quad (6)$$

From the 2D-PS trajectory formed by A and B, the attractors are quantified with the following four features:

Feat1: It is the summation of all the radial distances of each of the data points from the origin, given as:

$$\text{Feat1} = \sum_{k=1}^{N} \sqrt{{A_k}^2 + {B_k}^2}. \quad (7)$$

Feat2: It is the summation of all angles of data points for the x-axis measured in the anticlockwise direction. The Feat2 is defined as:

$$Feat2 = \sum_{k=1}^{N} \tan^{-1} \frac{B_k}{A_k}. \quad (8)$$

Feat3: It is defined as:

$$Feat3 = \sum_{k=1}^{N} \frac{|B_k + A_k||B_k + A_k|}{2}. \quad (9)$$

The above equation essentially represents the shortest distance between each point of 45- and 135-degree lines of rectangle edges formed between the origin and each data point in 2D-PS.

Feat4: For computing this feature, let us consider two successive points in 2D-PS with trajectories as $(A_k,\ B_k)$, (A_{k+1}, B_{k+1}), which defines the corner of the triangle for the origin (0,0). The Feat4 is the summation of these triangle areas computed as,

$$\text{Feat4} = 0.5 \sum_{k=1}^{N-2} \left| \det \begin{bmatrix} A_k & A_{k+1} & A_{k+2} \\ B_k & B_{k+1} & B_{k+2} \\ 1 & 1 & 1 \end{bmatrix} \right|. \quad (10)$$

In this manner, 4 features are mined from each VMF, resulting in 44 features per instance for 11 VMFs.

D. Butterfly Optimization Algorithm, (BOA)

Metaheuristic optimization techniques have gained much attention from research communities due to their fast convergence and interpretability [18]. In this work, we have used a popular metaheuristic algorithm for the feature selection tasks. In the following text, a brief on artificial butterfly optimization has been provided.

The BOA is inspired by the mate search approach of speckled wood butterflies, the BOA divides the solutions into two categories, namely, the sunspot and canopy. Initially, the population is initialized randomly as [19]:

$$Z_{i,j}^{t+1} = Z_{i,j}^{t} + \left(Z_{i,j}^{t} - Z_{k,j}^{t}\right).rnd(). \quad (11)$$

In Eq. (11), the $Z_{i,j}^{t}$ and $Z_{i,j}^{t+1}$ represent the butterflies at iteration number t and $t+1$. The j denotes the search space dimension. The $rnd()$ is a random number between +1 and -1. To update the butterflies, the following equation is used:

$$Z_{i,j}^{t+1} = Z_{i,j}^{t} + \frac{Z_{k,j}^{t} - Z_{i,j}^{t}}{\left\| Z_{k,j}^{t} - Z_{i,j}^{t} \right\|} (U - L) \times stp \times rnd(). \quad (12)$$

where the quantity $\left\| X_{k,j}^{t} - X_{i,j}^{t} \right\|$ shows the distance between the $Z_{k,j}^{t}$ and $Z_{i,j}^{t}$ butterflies with U and L representing the upper and lower bounds of search space. To control the exploration and exploitation, the step size is used, which is denoted as stp and consequently defined as:

$$stp = 1 - (1 - 0.02) \left(\frac{T_{current}}{T_{\text{maximum}}} \right). \quad (13)$$

where, the current and maximum number of iterations are denoted by $T_{current}$ and T_{maximum}, respectively. For binarization of the BOA, a thresholding-based approach has been utilized, wherein, the values greater than 0.5 are rounded off to 1 and less than 0.5 are rounded off to 0.

E. Classification

With the use of the mined and chosen feature set, the performance of two well-known and reliable supervised machine learning algorithms is evaluated in this study to identify SZ. The "k-Nearest Neighbor" (k-NN) and "Random Forest" algorithms are being taken into consideration (RF).

This decision was based on how frequently they were used in the literature for SZ detection. These classifiers' settings are adjusted incrementally while keeping in mind optimal performance. To avoid the limitation of dataset size on the performance of classifiers, the 1à-fold cross-validation scheme is followed. The biasness in findings is diminished by considering multiple evaluation measure criteria (cf. Section II-F).

1. **K-Nearest Neighbor (k-NN)**

The K-nearest neighbor (K-NN) is one of the most popular machine algorithms because of its simplicity and efficiency in pattern recognition. It classifies cases based on their similarities. K-NN takes the point with the lowest distance between the training point and the sample point. This classification is mostly implemented when all the attributes are continuous [20]. In this study, the model type is coarse k-NN and the number of neighbors, used to approximate each label is set to 3, the distance metric is Euclidean, and the distance weight is equal.

2. **Random Forest (RF)**

The Random Forest is an ensemble made up of many different decision trees. The relative priority that the random forest assigns to the input characteristics can be plainly seen, and it is frequently employed for classification problems.

It is a useful algorithm as its default hyperparameters frequently produce reliable predictions [21]. Some of its characteristics include Trees in a random forest can be de-correlated; it chooses the training sample and assigns a portion of the attributes to each tree; minimizing errors. A group of decision trees makes up a random forest. Individual tree mistakes and overall variation and error are reduced because random forest uses all the inputs from the trees to forecast the outcome of a particular row. Large data volumes can be handled: In addition to handling missing data well and managing vast volumes of data with higher dimensional variables, it can also manage outliers with little to no impact: Outlier data points may have a small influence on Random Forest since the outcome is determined by consulting numerous decision trees.

F. Evaluation Measures

1. **Optimization**

For evaluating the performance during optimization, we have used K-nearest neighbor with K=1 and classification accuracy as performance measure with the following equation:

Fitness= $Fitness = \beta \times error + (1-\beta)\frac{|F_{selected}|}{|F_{total}|}$. (14)

where the misclassification parameter is $error$ which is the value of accuracy subtracted from 1. The β is kept at a constant value of 0.99 to give more emphasis on classification accuracy. The selected and total number of features are denoted as $F_{selected}$ and F_{total}, respectively [22].

2. **Classification:**

There are several factors to consider when assessing a machine learning algorithm's performance. The algorithm's accuracy indicates how many cases were properly or wrongly predicted. There are four elements to this statement: the 'True Positive" (TP), "False Positive" (FP), "False Negative" (FN), and the "True Negative" (TN). The performance of classifiers is tested using multiple well-known measures given by:

$$Acc = \frac{TP+TN}{TP+TN+FP+FN}. \quad (15)$$

$$Sp = \frac{TN}{TN+FP}. \quad (16)$$

$$Se = \frac{TP}{TP+FN}. \quad (17)$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall}. \quad (18)$$

Where, the Acc, Sp, Se and F1 are the "accuracy", "specificity", "sensitivity" and "F-measure".

Two dimensions may be seen in the ROC curve graphic. On th e X-axis and the Y-axis, respectively, are depicted the false po sitive rate and the real positive rate. AUC stands for the region under the ROC curve [20]. The AUC is another metric used to assess performance.

III. RESULTS AND DISCUSSION

The results, obtained with the proposed method, are presented in this section. The whole chain is implemented by using the MATLAB® R2022b software. The signals from the frontal region EEG channels are segmented and concatenated. These are named instances.

Onward, each instance is decomposed into 11 VMFs. Examples of control and SZ instances and their corresponding 11 VMFs are respectively displayed in Fig. 2 and Fig. 3.

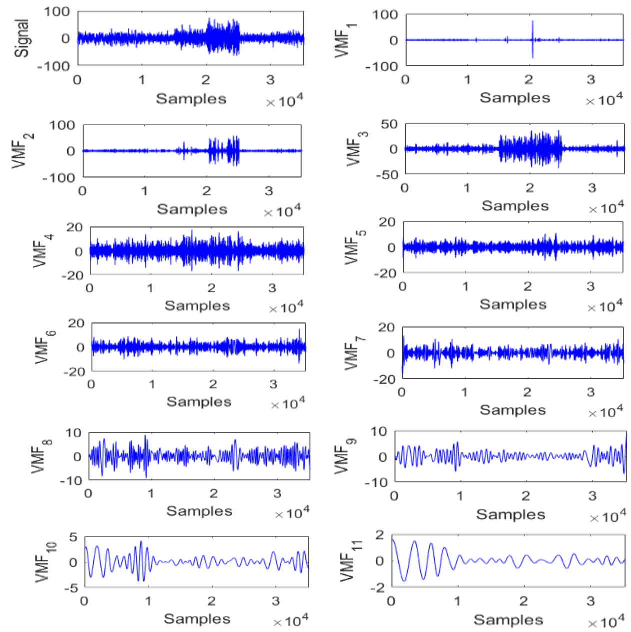

Fig. 2: Example of control instance and its 11 VMFs.

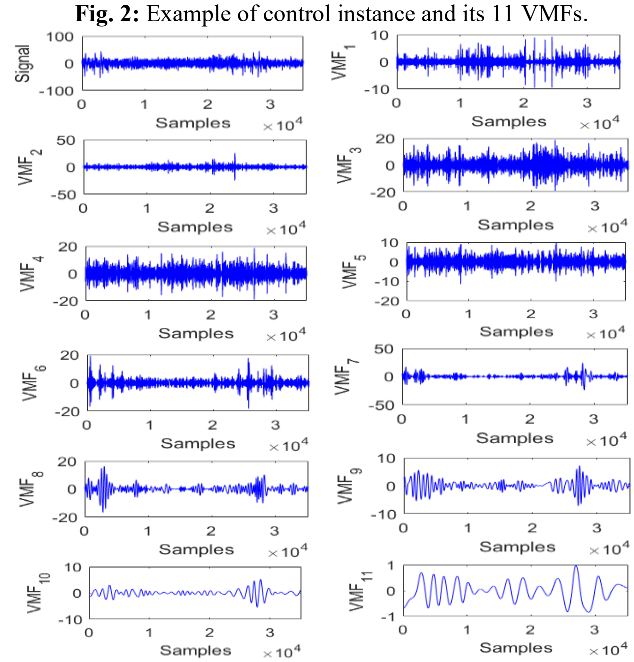

Fig. 3: Example of SZ instance and its 11 VMFs.

In the next step, 4 features are mined from each VMF, resulting in 44 features per instance. After BOA-based optimization, 11 features are selected per instance. The dimension reduction is carried out based on the fitness test. It renders a dimension reduction of 4 times and is beneficial in terms of data management, transmission, storage, and processing effectiveness [23].

The selected feature set is processed by the intended classifiers namely, k-NN and RF. The obtained classification evaluation measures are outlined in Tables 1 and 2.

Table I: *The [%age] evaluation measures for the k-NN classifier*

Measure	$A_{CC.}$	Sp.	Se.	F1	AUC
Ctrl	85.00	83.40	85.60	83.20	84.00
SZ	85.00	85.60	83.44	85.47	91.00
Avg.	85.00	84.52	84.52	84.33	87.50

Table II: *The [%age] evaluation measures for the RF classifier*

Measure	$A_{CC.}$	Sp.	Se.	F1	AUC
Ctrl	89.00	88.84	89.21	87.96	95.00
SZ	89.00	89.21	88.83	89.87	97.00
Avg.	89.00	89.02	89.02	88.92	96.00

Tables I and II show that the RF outperforms the k-NN classifier for the studied dataset and feature extraction and selection chain. On average, for both intended classes, the RF secures the A_{CC} score of 89.00%, Sp value of 89.02%, Se value of 89.02%, F1 score of 88.92%, and AUC value of 96.00%.

The average accuracy A_{CC} score of RF is 4% superior compared to the one obtained with k-NN. Both the Sp and Se values, obtained with RF, are 4.5% higher than the ones attained with k-NN. The F1 score of RF is 4.59% higher compared to the F1 score of k-NN. The AUC value of RF is 8.50% superior to the AUC value of k-NN. It confirms an outperformance of the RF over the k-NN. It is achieved due to the ensemble learning feature of the RF, as it diminishes the confusion of testing data labeling compared to the case of k-NN.

The performance of the devised solution is also compared with the previous contemporary studies. A summary of key findings and methods is presented in Table III. It shows that the devised solution attains a comparable or superior performance.

Table III: *Comparison with previous methods*

Study	**Classifier**	**Features Extraction.**	**Acc. (%)**
[11]	SVM	Sensor-level" and "source-level" features extraction	88.24
[14]	SVM	Welch power spectral density-based features extraction. Dimension reduction with Student's t-test.	88.00
[24]	2D-CNN-Long Short Term Memory (LSTM)	Not Applicable	72.54
[25]	RF	EEG time series based features	81.10
[26]	Ensemble Bagged Tree (EBT)	Kolmogorov complexity, approximate entropies, and Empirical Mode Decomposition (EMD) based characteristics	89.59
Proposed	**RF**	**VMD + RSC based features extraction. BOA based dimension reduction.**	**89.00**

The event-driven and signal-piloted processing based approaches can be beneficial in terms of the computational effectiveness, compression, consumption reduction, and diminishing in the hardware complexity [27], [28]. The feasibility if incorporating these tools, in the suggested method, can be investigated in future.

IV. Conclusion

In this paper, a new hybridization of segmentation, "Variational Mode Decomposition", "Rose Spiral Curve" based features extraction, "Artificial Butterfly Optimization Algorithm" based dimension reduction, and machine learning algorithms are devised for an effective schizophrenia detection. The multichannel EEG signals, from the frontal region, are segmented and concatenated to form an instance. Onward, each instance is decomposed into 11 VMFs and features from each VMF are mined. Four features are mined from each Mode using the base of the "Rose Spiral Curve" from each VMF. It rendered 44 features per instance. In the next step, the most pertinent features are selected, based on the fitness test, using the "Artificial Butterfly Optimization Algorithm". It renders 11 selected features per instance. The selected features it is processed by the considered machine learning-based classifiers. The devised model secures 89.00% average accuracy for the case of the Random Forest classifier. A comparison is also made with previous related studies. It is shown that the performance secured by the devised method is comparable to the counterparts.

In this study, only the signals from frontal region are examined. In future, the EEG signals from other regions like central, temporal and occipital will be examined and the findings will be analyzed and compared. Moreover an optimized selection and hybridization of multi-region EEG signals will be investigated in the aim of attaining the best SZ identification performance while employing a minimum number of EEG signal channels. The evaluation measures clarify the performance of a classifier. However, the performance of the classifier will differ according to the employed dataset. Many factors contribute to the outcome and accuracy result. These results will vary when using different datasets, feature extraction methods, dimension reduction approaches, and classification algorithms. In the future, the performance of devised method will be studied while incorporating other decomposition, feature mining, and dimension reduction approaches. Another prospect is to explore the performance of robust ensemble and deep learning models for categorizing the mined dataset. Moreover, the feasibility of applying this method to other EEG datasets will be explored in the future.

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