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Original Article

Application of Hjorth parameters in the classification of healthy aging EEG signals♣

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Abstract

Aging has extensive impacts on brain cognition. In this work we proposed a method using Hjorth parameters to classify the elderly's electroencephalography (EEG) signals from that of middle age group by applying K-nearest neighbor (KNN) and Random forest (RF) classifiers. We acquired EEG of 20 healthy middle age subjects and 20 healthy elderly subjects in resting state eyes-open for 5 minutes and eyes-closed for 5 minutes using an 8-electrodes device. Euclidean and Manhattan distance measures were tested using KNN. The classifier performance was evaluated by using accuracy, sensitivity, specificity, and kappa statistic. The best accuracy achieved was 91.25 %, and kappa statistic of 0.825, in eyes-closed state. In eyes-open state 90% accuracy was achieved with kappa statistic of 0.80. RF achieved 83.75% accuracy with kappa statistic of 0.675 in eyes-closed state and 78.75% accuracy with Kappa statistic of 0.575 in eyes-open state. The KNN performed better using Manhattan distance function in both eyes-open and eyes-closed states. Results showed the potential of Hjorth parameters as the suitable EEG features in the classification of EEG aging signals.

Keywords: electroencephalography, aging, Hjorth parameters, k-nearest neighbor, classification

1. Introduction

The increasing proportion of older age people in the population has attracted the interest in research on aging (Dushanova & Christov, 2014). Aging is considered a major risk factor of Alzheimer's disease (AD). Several neuro imaging techniques applied to investigate the pathological and physiological aging and age related issued, including functional magnetic resonance imaging (fMRI), positron emission tomography (PET), magneto encephalography (MEG) and electroencephalography (EEG) (Ishii *et al.*, 2017). Several measures have been applied to investigate the changes in EEG signals. Time domain and frequency domain features have been calculated including advance features such as entropy, fractal dimension and network features to study the EEG alteration (Petti *et al.*, 2016; Takahashi *et al.*, 2009; Zappasodi, Marzetti, Olejarczyk, Tecchio, & Pizzella, 2015). It is very crucial to investigate the age-related changes in

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healthy older population who are more vulnerable to neurodegenerative disease.

To discriminate the elderly age EEG signal from young adult, feature extraction and classification techniques have been applied in the recent studies (Al Zoubi *et al.*, 2018; Petti *et al.*, 2016). Most of the recent studies have investigated the differences between old age adults and young age adults. There is a gap to investigate the differences between the EEG signals of an elderly age group and a middle age group. The spectral analysis of EEG aging signals is limited and for further advance analysis is required to develop a clinical tool for the better understanding of healthy aging signal and the link between the healthy elderly EEG and initiation of dementia. EEG is high temporal resolution, cost-effective and non-invasive technique. It is being used to investigate the structural and functional organization of brain.

The EEG frequency and band power differ in eyes-open and eyes-closed states. It has demonstrated that eyes-open and eyes-closed states show differences in EEG measurements in topography and bands power (Barry, Clarke, Johnstone, Magee, & Rushby, 2007). Moreover, the alpha activity was found dominant in eyes-closed state and it was suppressed in eyes-open state with visual stimulation (Barry *et al.*, 2007). The heathy older participants showed reduction in alpha activity as compared to healthy young subjects in posterior and central region in open and close eyes (Barry & De Blasio, 2017). In resting state, EEG slowing is a distinguished characteristic of healthy elderly in both eyes-open and eyes-closed states (Giaquinto & Nolfe, 1986). The alterations in EEG activity are well known in eyes-open and eyes-closed states and resting EEG demonstrates age-dependent changes throughout the life span.

Hjorth parameters are high order statistical time domain features (Hjorth, 1970; Leite & Moreno, 2018). Hjorth parameters have been applied in many applications. For example, Hjorth parameters have been used to asses a semi-automatic method for temporal lobe seizure lateralization using EEG (Cecchin *et al.*, 2010). Hjorth parameter based technique has been introduced to detect the insomnia from EEG signals (Hamida, Ahmed, & Penzel, 2015). To classify the mild cognitive impairment patients from healthy subject Hjorth parameters achieved 80% accuracy (Hadiyoso & Tati, 2018). In emotion recognition study, Hjorth parameters were effective to represent the event related properties of EEG and SVM achieved 70% of accuracy (Mehmood & Lee, 2015a). Hjorth activity and mobility have been used to design the method for laterization of seizure using raw EEG (Cecchin *et al.*, 2010). As compared to frequency domain analysis, Hjorth parameters can be easily calculated with less computational cost, which makes them useful in real time application with reduced resources (Hjorth, 1973). The short time Fourier transform and wavelet techniques are useful to analyze the non-stationary signals, but contain large number of data points cause difficulties in classification including the increased computational complexity cost and risk of overfitting. Hjorth parameters have used to overcome these issues for the classification of non-stationary signals (Kaboli, Walker, & Cheng, 2015). Furthermore, Hjorth parameters use frequency content of EEG signals, and are dependent on band power so it makes them robust to non-stationarities (Vidaurre, Krämer, Blankertz, & Schlögl, 2009).

Several machine learning models have been developed to classify the neurodegenerative diseases such as AD and Parkinson's disease (Das, 2010; Lehmann *et al.*, 2007). K-nearest neighbor (KNN) has been widely applied in EEG research studies including brain computer interface, epilepsy, autism, emotion recognition and AD (Sha'abani, Fuad, Jamal, & Ismail, 2020; Al-Nuaimi, Jammeh, Sun, & Ifeachor, 2017). An EEG-based Concealed Information Test was developed and KNN achieved 96.7% accuracy using Hjorth parameters (Bablani, Edla, & Dodia, 2018). KNN has been also utilized to automatically classify sleep stages from a single channel EEG using three distance measures (Qureshi, Karrila, & Vanichayobon, 2018). A pervasive EEG-based depression detection system was designed and KNN achieved highest accuracy of 79.27% (Cai *et al.*, 2018). Random forest (RF) was applied on several EEG features including Hjorth parameters and provided 98.1% overall accuracy to classify the human emotions (Vaid, Singh, & Kaur, 2015). RF has been used effectively to develop the sleep stage scoring techniques based on EEG (Bi, Liao, & Lu, 2018; Boostani, Karimzadeh, & Nami, 2017).

Aging is considered as a major risk factor in cognitive decline (Salat, 2011). The researchers have lighted the crucially needed biomarker of brain aging to understand the aging mechanism and identify those individuals who are at risk to age-related neurological disorders, cognitive decline and death (Paixao *et al.*, 2020). The design of comprehensive and effective tools is needed to improve the brain health. It is necessary to investigate the age-related decline in healthy aging and the association of aging with mild cognitive impairment and dementia. The features and classification of EEG in healthy aging may provide better understanding of aging process and basis of age-related cognitive decline to improve the wellness of aging population.

In this work, we proposed Hjorth parameters-based technique by applying KNN and RF to classify the EEG aging signals of elderly age versus middle age in the eyes-open and eyes-closed resting conditions. We further compared the performance of these two classifiers.

2. Materials and Methods

In this work we recorded EEG in eyes-open and eyes-closed states for 5 minutes each. Preprocessing was applied on EEG data to clean the data. Feature extraction technique was applied to extract the Hjorth parameter as EEG features and KNN and RF classifiers were employed to classify the data as shown in Figure 1.

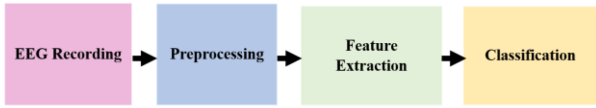


Figure 1. Illustration of main steps involved in experiment

2.1 EEG recording and preprocessing

This study was approved by the ethics committee of Prince of Songkla University, Songkla, Thailand (HSC-HREC-61-006-02-1). Participant who had no neurological disorder and could communicate were considered as healthy subject. There were forty healthy subjects in this study. They were divided into two groups of 20 middle age subjects (age range, 41 to 60 years; mean age 50.50±5.77 years) and 20 elderly subjects (age range, 61 to 84 years; mean age 71.03±5.45 years) as shown in Table 1. All participants signed an informed consent form and had no neurological disorder. We used Ultracortex Mark IV headset (OpenBCI, New York, USA) with eight electrodes FP1, FP2, C3, C4, P7, P8, O1 and O2 according to 10-20 international electrode placement system. EEG sampling rate was 250 Hz and impedance was kept below 5 kΩ. Infinite impulse response (IIR) 50 Hz notch filter was used to remove the line noise. EEG was filtered using 2nd order Butterworth filter at 0.5 Hz to 45 Hz. EEG was divided into delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (13-30 Hz) and gamma (30 -45 Hz). MATLAB R2019b (Mathworks Inc., Natick, USA) was used for analysis. Examples of raw EEG signals recorded from middle aged and elderly from FP1, C3, P7, and O1 electrodes are shown in Figure 2.

2.2 Hjorth parameters

Hjorth parameters are time domain indicators used for the analysis of signals and features extraction process. Hjorth parameters have been used in recent studies in EEG, electrocardiogram (ECG) and electromyogram (EMG) (Mouzé-Amady & Horwat, 1996; Rizal & Hadiyoso, 2015; Vidaurre *et al.*, 2009). Hjorth parameters have three features included activity, mobility, and complexity and they can be computed for EEG signals (Vidaurre *et al.*, 2009). Activity parameter represents the power in the signal (s(t)), variance in time domain as shown in equation (1).

$$\text{Acitvity} = var\,(\text{s(t)}) \tag{1}$$

Mobility represents the mean frequency of the signal, and it can be calculated from the square root of the ratio of the variance of the first derivate of the signal (s' (t)) and the variance of the signal as shown in equation (2) (Grover & Turk, 2020).

$$\text{Mobility} = \sqrt{\frac{var\,(\text{s}'(\text{t}))}{var\,(\text{s(t)})}} \tag{2}$$

The complexity parameter represents the changes in the frequency. Complexity is the ratio of the mobility of first derivative of signal (s' (t)) divided by the mobility of the signal (s(t)), and it can be calculated by using the equation (3).

$$Complexity = \frac{\text{Mobility (s}'\text{(t))}}{\text{Mobility (s(t))}} = \sqrt{\frac{var(\text{s}''(\text{t}))}{var(\text{s}'(\text{t}))} \Big/ \frac{var(\text{s}'(\text{t}))}{var(\text{s(t)})}} \tag{3}$$

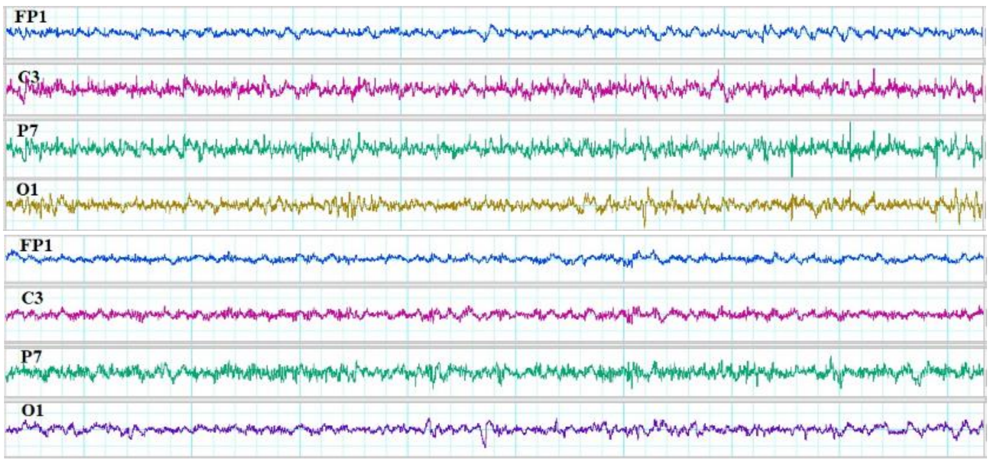
2.3 K-nearest neighbor

K-nearest neighbor (KNN) is a simple non-parametric machine learning model based on supervised learning. KNN is also called learner algorithm, as instead of learning it stores the dataset and it performs action at the time of classification. KNN has been employed in EEG analysis using Hjorth indicator as input features for classification (Bablani *et al.*, 2018; Mehmood & Lee, 2015b).

Table 1. Demographic details of participants

Group	Middle aged		Elderly	
Gender	Male	Female	Male	Female
Number of subjects	9	11	8	12
Age (years)	45.51±6.21	53.11±4.11	71.75±4.60	71.15±7.34

Data are mean ± SD



(a)

(b)

Figure 2. Examples of raw EEG of electrode FP1, C3, P7 and O1: (a) Middle aged, (b) Elderly

We calculated Hjorth parameters of EEG signals and tested KNN to discriminate the two age groups: middle aged and elderly. We tested Euclidean and Manhattan distance values K =1, 3, 5, 7, and 9. Euclidean distance (D_E) and Manhattan distance (D_M) are calculated using the equation (4) and (5) (Gao & Li, 2020).

$$D_E = \sqrt{\sum_{I=1}^{n} (X_i - Y_i)^2} \tag{4}$$

$$D_M = \|X - Y\|_2 = \sum_{i=1}^{n} |X_i - Y_i| \tag{5}$$

2.4 Random forest

Random forest (RF) is a useful modification of bagging, and it builds a large combination of de-correlated trees and the average those trees (Hastie, Tibshirani, & Friedman, 2001). RF utilizes the majority vote to predict the classes based on the separation of data from multiple decision trees. Bagging and random selection of features are used to grow the multiple trees (El Bouchefry & de Souza, 2020). The RF classifier consists of randomly selected features at each node to grow a tree. Bagging is a technique used to reduce the variance of as estimated prediction function and it is considered as suitable for low-bias procedures and high variance such as tree(Hastie *et al.*, 2001). RF has been used for the classification of EEG signals for an emotion recognition (Vaid *et al.*, 2015) and a sleep stage classification (Bi *et al.*, 2018).

The RF algorithm applies the general technique of bootstrap aggregation also called bagging to tree learners. For a training set $X = x_1, x_2, x_3, \ldots \ldots \ldots x_n$ with the responses obtained as $Y = y_1, y_2, \ldots \ldots \ldots y_n$ and bagging (B times) selects the random sample from sample data and fits the trees to these selected samples (Breiman, 2001).

For b=1,...,B:

1) Samples with replacements, N training samples from X, Y are called Xa, Xb.

2) Classification tree f_b is trained on Xa, Xb.

After the training, to make a prediction to a new point, s' can be obtained by averaging the predictions from all the individual tree on s' as sown in equation (6) (Breiman, 2001).

$$\hat{F} = \frac{1}{B} \sum_{b=1}^{B} f_b(s') \tag{6}$$

2.5 Classification performance

The 10-fold cross validation was used in this work. The classification performance was evaluated using accuracy (Acc) in equation (7), sensitivity (Sn) in equation (8), specificity (Sp) in equation (9), and Cohen's kappa value (Ks) in equation (10).TP and TN, represent the true positive and true negative and FP, FN represent false positive and false negative, respectively. Pa indicates the probability of observed agreement and Pb shows the probability occurred by chance, whereas the value Ks ≥0.75 generally shows an excellent agreement. Receiver operating curve (ROC) value was computed. ROC value is calculated with true positive rate (sensitivity) against a false positive rate (1-specificity). The area under the ROC curve (AUC) is the numerical index used to describe the behavior of ROC curve as defined in equation (11) (Calì & Longobardi, 2015).

$$\mathrm{Acc} = \frac{(\mathrm{TP} + \mathrm{TN})}{(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})} \times 100\% \tag{7}$$

$$\mathrm{Sn} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \times 100\% \tag{8}$$

$$\mathrm{Sp} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \times 100\% \tag{9}$$

$$\mathrm{Ks} = \frac{P_a - P_b}{1 - P_b} \tag{10}$$

$$\mathrm{AUC} = \int_0^1 \mathrm{ROC}\ (\mathrm{t})\mathrm{d}(\mathrm{t}) \tag{11}$$

3. Results and Discussion

In this work we used 10-fold cross validation in classification. EEG signals were recorded in eyes-open and eyes-closed states. Hjorth parameters were calculated and KNN and RF were used to classify the EEG signals of middle aged and elderly. Table 2 shows the comparison of Euclidean and Manhattan distance measures for the distance value of K=1, 3, 5, 7, and 9 in eyes-closed and eyes-open state. For K=1, KNN obtained highest accuracy of 91.25±4.11% using Manhattan distance measure and 91.25±4.87% accuracy with Euclidean distance measure. In eyes-open state for K=1, 90.00±5.40% accuracy was achieved by using Manhattan distance measure while the accuracy of 83.75±6.02% was achieved with Euclidean distance measure. The RF achieved 78.75±13.97% accuracy in eyes-open state and 83.75±12.36 % accuracy in eyes closed state. However, in both eyes-open and eyes-closed states, Manhattan distance measure produced higher accuracy compared to Euclidean distance measure. Our results showed that the classification accuracy was reduced with higher value of K. This work achieved a highest classification accuracy when K=1 with low classification errors.

The overall accuracy in both eyes-open and eyes-close states by using KNN and RF is shown in Figure 3. KNN has achieved better accuracy in eyes-open and eyes-closed states as compared to RF classifier. The highest overall accuracy was achieved 91.25% and 90.00% at K=1 in eyes-closed and eyes-open, respectively. Our work has a similar finding to other studies that using KNN with K=1 provides highest accuracy. For example, a recent study of Parkinson's disease detection system obtained accuracy of 96.54 % using KNN with K=1 (Chen *et al.*, 2013). By using power spectral density features, KNN obtained highest accuracy with K=1 (Moosavian, Ahmadi, Tabatabaeefar, & Khazaee, 2013). In

Table 2. Classification results 10-fold cross-validation

Classifier	State	Accuracy (%) ± standard deviation				
		K=1	K=3	K=5	K=7	K=9
KNN (Manhattan)	Eyes open	90.00±5.40	81.25±6.51	81.20±6.51	71.25±8.21	73.75±7.89
	Eyes-closed	91.25±4.11	82.50±6.46	82.50±6.21	83.75±7.06	52.50±7.35
KNN (Euclidean)	Eyes open	83.75±6.02	81.20±6.84	75.00±6.94	70.00±7.91	73.75±8.40
	Eyes-closed	91.25±4.87	81.17±6.06	81.25±7.20	76.25±6.98	81.20±6.60
RF	Eyes open			78.75±13.97		
	Eyes-closed			83.75±12.36		

Data are mean ± SD

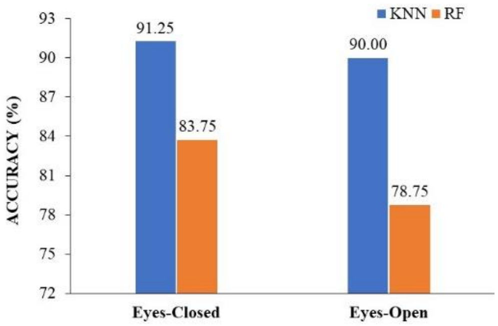


Figure 3. Accuracy of KNN and RF in eyes-closed and eyes-open

the comparison of resting state, eyes-closed was found more effective in the classification of aging signals. Manhattan distance measure improved the accuracy in eyes-open and was found effective in eyes-closed states as well.

Table 3 shows the classification results including sensitivity, specificity, ROC value and Cohen's Kappa value in both eyes-open and eyes-closed states. Classification parameters show the evaluation of KNN in both states. The highest area under the ROC curve value of 0.916 for eyes-closed state and 0.906 for eyes-open state were obtained using KNN and RF, respectively. Kappa values show the excellent performance of classification model by using KNN. In comparison of classification performance KNN showed better sensitivity, specificity and kappa values compared to RF.Hjorth parameters have been used in this work as features to extract the information from EEG signals. The classification results show the efficacy of Hjorth parameters in the discrimination of EEG signals in aging. Sensitivity values of 0.913 in eyes closed state and 0.900 in eyes-open state show the correctly identified instances of both classes. Sensitivity and specificity results verify the highest accuracy achieved in open and close eyes as shown in Table 3.

In previous study, KNN has shown highest classification performance with sensitivity and specificity >90% in resting state condition for the detection of MCI using EEG (Siuly *et al.*, 2020). For the discrimination of Alzheimer's disease, KNN obtained the sensitivity and specificity of 100% and 80% respectively under the resting state condition(Al-Nuaimi *et al.*, 2017). In the EEG-based depression detection study, KNN classification performance was better than RF and other classifiers (Li, Hu, Sun, & Cai, 2016). KNN demonstrated a better classification result compared with RF in EEG based automatic seizure detection system (Slimen & Seddik, 2020).

An effective Parkinson's disease detection system was designed using fuzzy-KNN and reported sensitivity and specificity of 96.25% and 95.07% respectively (Chen *et al.*, 2013). In the investigation of age alteration of electrical activities of young versus old, Hjorth parameters and fractal dimension were found higher in older participants (Portnova, 2018). In our study, Hjorth parameters were used as input features and we obtained highest accuracy of 91.25% to discriminate the aging EEG signals.

It is important to understand and investigate the transitional stage between normal healthy aging and neurodegenerative diseases such as mild cognitive impairment (MCI) and Alzheimer's disease (AD). In order to investigate MCI transition to AD, Poil and colleague used Hjorth parameters to develop the EEG biomarker for AD prediction system and obtained sensitivity of 88% and specificity of 82% (Poil *et al.*, 2013). In our current study we achieved sensitivity and specificity of >90% in eyes-closed and 90% in eyes-open state. In recent studies, magnetic resonance imaging (MRI) and functional MRI (fMRI) have been used to investigate the age prediction using machine learning techniques (Dosenbach *et al.*, 2010; Valizadeh, Hänggi, Mérillat, & Jäncke, 2017). The current study proposed a simple and useful technique using EEG which is economical and portable as compared to MRI and fMRI.

Age prediction has been performed using different techniques including EEG signals analysis and brain anatomical measurement (Al Zoubi *et al.*, 2018; Valizadeh *et al.*, 2017). A machine learning model was designed to predict the brain aging using nested cross-validation approach and prediction model and achieved R^2 = 0.37 resting state EEG (Al Zoubi *et al.*, 2018). A recent study performed the classification of young versus middle aged adults obtained R^2 = 0.60 with an accuracy of 87.2% in resting state open eyes, but the study excluded elderly subjects (Dimitriadis & Salis, 2017). The graph theory network features were utilized to classify the young and middle age groups and SVM achieved accuracy ranging from 82% to 89% in resting state brain network analysis (Petti *et al.*, 2016). Our study achieved accuracy of 91.25% which is higher than previous studies to the best of our knowledge. Moreover, the application of only three features (Hjorth parameters) is also advantageous in order to reduce the computational cost (Hjorth, 1970; Kaboli *et al.*, 2015).

Table 3. Classification results of middle aged versus elderly in eyes-closed and eyes-open states

Classifier	State	Sensitivity	Specificity	ROC Area	Kappa-statistic
KNN	Eyes-closed	0.913	0.912	0.908	0.825
	Eyes-open	0.900	0.900	0.906	0.800
RF	Eyes-closed	0.838	0.837	0.916	0.675
	Eyes-open	0.788	0.787	0.871	0.575

We calculated sample entropy as EEG feature in eyes-open and eyes-closed states and performed classification using KNN and RF classifiers (Table A1 in the Appendix). The classification results of sample entropy were compared with the classification results obtained with Hjorth parameters. The highest accuracies with sample entropy achieved via KNN classifier were 73.75% with K=3 in eyes-open state using Euclidean distance measure and 77.50% with K=1 in eyes-closed state using Manhattan distance measure. The accuracy of RF classifier provides 72.50% in eyes-closed state and 70% accuracy in eyes-open state. Therefore, the classification results of Hjorth parameters are better than the results obtained from sample entropy.

In this preliminary work, we have proposed a useful feature set merged with KNN classifier to distinguish the elderly age group using brain electrical activities. The effectiveness of EEG resting state has also been illustrated. The eyes-closed state has shown more prominent results in Table 2. KNN signified the potential of Hjorth parameters in the study of aging EEG signals better than RF.

4. Conclusions

This preliminary work presented the research on classification of EEG signal of middle age group and elderly age group in eyes-open and eyes-closed resting state using 8-channels device. Three Hjorth parameters, activity, mobility, and complexity were used. KNN and RF classifiers were applied on these features to classify the EEG data. KNN achieved the accuracy of 91.25% in eyes-closed and 90% accuracy was achieved in eyes-open state using 10-fold cross validation. In our next study, we plan to include young subject to find the comprehensive correlation of EEG signals with aging.

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Appendix

Table A1. Classification results of sample entropy

Classifier	Value of K	State	Accuracy (%)	Sensitivity	Specificity	Kappa Statistic
RF	N/A	Eyes-closed	72.50	0.725	0.720	0.425
		Eyes-open	70.00	0.725	0.675	0.400
KNN (Euclidean)	1	Eyes-closed	71.25	0.713	0.712	0.425
	3	Eyes-open	73.75	0.738	0.737	0.475
KNN (Manhattan)	1	Eyes-closed	67.50	0.675	0.674	0.300
	1	Eyes-open	77.50	0.775	0.770	0.550