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CLINICAL STUDY

Mental arithmetic task detection using geometric features extraction of EEG signal based on machine learning

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ABSTRACT

BACKGROUND: Mental arithmetic analysis based on electroencephalogram (EEG) signals can help to understand some disorders such as attention deficit hyperactivity disorder, arithmetic disorder, or autism spectrum disorder in which learning is difficult. Most mental computation detection and classification systems rely on the characteristics of a single channel, however, the understanding of the connections between EEG channels, which certainly contains valuable information, is still evolving. The methods presented in this paper are the result of a research project that introduces an alternative method for better and faster receipt of information from the EEG signals of individuals, which are generally complex and nonlinear.

METHODS: The EEGs of 66 healthy individuals were recorded in two rest modes and mental task a designed, with a sampling frequency of 500 Hz. To classify these two modes, we extracted features from our recordings to differentiate the EEG signals of these two groups in a single channel as well as combine possible channels. The new method that was proposed was the extraction of several geometric features from Poincaré design analysis, which used the necessary comparison t-test to determine brain differences, with a significance level of less than 0.05 in the state of mental calculations and facial rest. Also, an artificial neural network (ANN) has been used for automatic learning and diagnosis in the two mentioned modes.

RESULTS: The results of this paper show that by using a combination of geometric properties (sides, angles, shortest distance, slope, and coefficients of the third-degree equation) using selected channels (FP1, F7, C4, O1) can achieve 100 % accuracy. The sensitivity reached 100 %. As well as 100 % feature.

CONCLUSIONS: With the help of mental calculation, it is possible to diagnose, treat, rehabilitate and rehabilitation people who have lost the function of a part of their brain due to a disease in this field *(Tab. 6, Fig. 15, Ref. 45)*. Text in PDF *www.elis.sk*

KEY WORDS: EEG, mental arithmetic task, artificial neural network, geometric features, classification.

Introduction

Mental tasks include reality retrieval, memory, sequencing, and decision making. Automatic detection of such activity through EEG signals helps to understand the brain's response to these cognitive tasks (1). Mental tasks are considered to be a very good stimulus for the brain, which simultaneously promotes development in both hemispheres of the brain and brain balance. The basic activities of cognitive functions are very important to us (2). In the past decades using the meta-analysis method functional magnetic resonance imaging (fMRI) areas of the brain that are in between mental task (calculated with numbers) is identified and found to work in a set of common areas such as the lower parietal lobule become inferior (3). Researchers' studies to show important aspects of the brain-behavior show that for early detection of mental disorders, mild cognitive disorders and mental disorders such as Disklaklia in cases such as math perception, attention deficit hyperactivity disorder as well as autism spectrum disorders with attention deficit disorder at the same time, it is useful to use the analysis of the electrical activity of the brain during mental activity (4–5).

Adel Deniz Doro and his colleague applied 16 EEG signals to ten elite athletes and ten non-athletes in two rest modes with their eyes closed and the second mode, including mental subtraction task, using Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS) with neural efficiency with Recorded the use of mental tasks. They concluded that when people do mental tasks, the strength of the theta band is greater in the anterior regions than in the frontal sites. While for the alpha group, the posterior regions have higher values than the frontal sites, which compared to non-athletes, the strength of the posterior alpha band was higher (6). The focus of further studies is on a complex approach to the analysis of mental activity and cognitive function (7). One of the major problems in classifying mental tasks is the sensitivity of signal recording equipment to artifacts that are affected by noise; Is. To solve this problem, the

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multi-channel convolution neural network architecture, whose classification accuracy is approximately 70%, is superior to other alternative methods (8).

Zachary et al used three methods of spectral estimation Wiener-Khinchine)w_k(, autoregressive (AR), and Borg method on five people in two sessions by performing five different mental tasks to classify between different mental tasks using only EEG signal. The results show that it is possible to accurately separate both sessions from the five mental tasks studied with high accuracy (9). In the design of brain-computer interface (BCI) systems, the features extracted from the low-frequency bands of EEG signals recorded on the scalp are usually considered to classify subjective calculations (10). Pengfi Wei also examined the difference between mental work and other tasks such as reading with two methods using conventional EEG signal estimation as an AR process and another method without calculating spectral density using only AR coefficients. That mental work is faced with an increase in delta frequency, while this trend is reversed in the theta band (10).

Identifying and classifying mental tasks with a single-channel EEG signal plays an important role in BCI. Manali Saini and his colleague used a lightweight one-dimensional convolutional neural network to identify the mental task and classify two different cases (baseline binary classification, mental multi-tasks classification) using a noise-free EEG signal. The result of their study was 99.7 % accuracy for binary classification and 100 % for mental multi-classification (11). Of course, some challenges, such as network measurement in terms of brain structure and function, linking neural network features to more direct computing, and integrating networks at spatial scales, are opportunities to go beyond current applications (12). Mental proficiency was assessed for EEG signal disorders. Many neurological diseases (such as epilepsy) can be detected by studying EEG signals. However, recording the noise signal can have a detrimental effect on the original signal. After removing the noise and recording the signal with three steps of preprocessing, selecting, and classifying the features, important information can be extracted from the signal information used for classification (13–14).

Previous studies show; to examine the properties of the brain network when performing calculations with two concepts between multiplex and betweenness centrality were able to explain the functional structure of the brain, yet in evaluation band power during mental tasks, they found that mental tasks increase delta band power and decrease beta, as well as increase alpha in the frontal region (15–16). Bert De Smedt and his colleagues studied how the brain activates during addition and subtraction of single-digit numbers on 28 children at several levels of arithmetic mastery commensurate with adult data using the FMRI method, and observed that children with a low level of mastery, more activation on the right Intra-permeable sulcus were obtained during the task (17).

Maghsoudi and his colleagues by using the Global and Professional Direct Contracting (GPDC) method on 29 healthy participants worked to extract the distinctive features of effective brain connection and to create a hierarchy for classifying and discriminating mental arithmetic tasks versus rest. It was also observed that by analyzing the brain network during the mental tasks of EEG signals, shown in the frontal and prefrontal areas especially AFP2, AFP1 has separation High flexibility and effective connectivity vary, and these areas play a role in the visual recognition of numbers and are essential for mental Arithmetic Task. The cognitive workload is also performed in the frontal cortex (18). Fouladi Dehaghi and his colleagues for early diagnosis of mental fatigue with a fast Fourier transform (FFT) method for 20 people who recorded brain waves without activity and second stage with a mental activity using EEG signals (specifying the number of literary text errors) and observe that the reduction of brain waves indicates mental fatigue (19).

Movahedi and his colleague used the multivariate analysis of variance on 40 boys to analyze the cognitive activity of the brain while thinking in two stages of rest and perform a creatively designed test to record the EEG signal. The results of their study were that in the frontal, central and parietal region during creative cognitive thinking, the alpha band rate is higher and in the temporal region the delta band rate is higher and in the other frequency bands in other brain regions, no change was observed (20). Dengfeng Huang et al using Granger causality (GC) based Partial directed coherence (PDC) on 19 healthy individuals to evaluate effective brain networks during two different mental tasks (rest mode and play on the computer), they recorded the EEG signal and observed that local efficiency in Beta frequency increases and decreases in theta frequency, and also during activity, theta frequency increases and the beta frequency decreases (21).

The EEG signal could also help physicians diagnose children with attention-deficit hyperactivity disorder (ADHD) and healthy individuals when performing a continuous mental task. According to previous studies, this work was investigated using nonlinear features and multi-layer perceptron (MLP) (22); But with the development of the deep learning model using convolutional neural network (CNN) and EEG, they were able to achieve an accuracy of 98.48 % (23). Thilakvathi et al of 78 people, including 23 normal people and 55 people with schizophrenia, were able to identify schizophrenics at rest and with mental activity by the EEG signal complexity during a mental task. Shannon entropy (ShEn), spectral entropy (SPEn), Information entropy (InEn), Higuchi's Fractal dimension (HFD), glomograph complexity, and Approximate Entropies (APEn) were used for further analysis for all 16 channels. In this paper, they used visual stimuli to stimulate mental activity. They concluded that the parameters selected were higher for people with schizophrenia than for normal people during a mental task. Also, the parameters (APEn, InEn, HFD, Kolmogorov Complexity (KOL) have higher values, and ShEn and SPEn measurements have lower values than normal people (24–25). The power spectral density (PSD) estimation or approach is used to calculate the intensity of cortical activity and to evaluate the quantity of connections between different regions of the brain. Also, for studying changes in brain dynamics activation density of the power spectrum or during mental arithmetic task detrended fluctuation analysis (DFA) trend analysis method efficient, DFA is a scale-free method used as a measure of EEG durability over time. This method by Ivan Seleznov and his colleagues was performed on 36 people with 4 domains and found that long-term correlations measured by DFA

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could be considered in the future to diagnose the causes of many types of brain disorders (26).

The purpose of this study was to detect mental activity with a standard single electrode EEG signal 20_10 and with using the non-static and nonlinear nature of the EEG signal, which is based on frequency-domain methods and we use the time to decompose the signal into different bands. Study in this field in addition to applications a clinic that can have mental disorders in the field of timely diagnosis and treatment, in science BCI-based plays an important role and makes many advances in this area.

In this study, we use the analysis of the relationship between selected brain channels and its p_value calculation, one of the methods of evaluation is to check the activity of different areas of the brain when making mental tasks. These studies were performed on 23 brain channels when subtracting 4-digit numbers from 2-digit numbers. The purpose was to answer the question of whether there is a significant difference between different areas of the brain when a person is mentally calculating and when a person is at rest. We used the ANN modeling method to create effective networks related to neural activity.

Tab. 1. Data specifications.

Participant	Age	Gender	Number of Subtractions	Count Quality
Subject0	21	Female	9.7	B
Subject1	18	Female	29.35	G
Subject2	19	Female	12.88	G
Subject3	17	Female	31	G
Subject4	17	Female	8.6	B
Subject5	16	Female	20.71	G
Subject6	18	Male	4.35	B
Subject7	18	Female	13.38	G
Subject8	26	Male	18.24	G
Subject9	16	Female	7	B
Subject10	17	Female	1	B
Subject11	18	Female	26	G
Subject12	17	Female	26.36	G
Subject13	24	Male	34	G
Subject14	17	Female	9	B
Subject15	17	Female	22.18	G
Subject16	17	Female	11.59	G
Subject17	17	Female	28.7	G
Subject18	17	Female	20	G
Subject19	22	Male	7.06	B
Subject20	17	Female	15.41	G
Subject21	19	Female	4.47	B
Subject22	20	Female	1	B
Subject23	16	Female	27.47	G
Subject24	17	Male	14.76	G
Subject25	17	Male	30.53	G
Subject26	17	Female	13.59	G
Subject27	19	Female	34.59	G
Subject28	19	Female	27	G
Subject29	19	Male	16.59	G
Subject30	17	Male	10	B
Subject31	19	Female	19.88	G
Subject32	20	Female	13	G
Subject33	17	Male	21.47	G
Subject34	18	Female	31	G
Subject35	17	Female	12.18	G

In the second part, we will introduce the conditions and how to perform the experiments, as well as the method of data analysis, and the proposed method will be described. The third part is dedicated to the description of the simulation results, in the fourth part we discuss, and finally, in the fifth part, we summarize the study.

Materials and methods

Data description

Sixty-six healthy right-handed individuals (47 females and 19 males) initially participated in this study. Based on EEG visual inspection by an electronics neurologist, 30 of the 66 initial participants were excluded from the database due to poor EEG quality (excessive number of ocular and muscular artifacts), so the final sample size was 36 people (27). All participants (75 % female and 25 % male with a mean age of 18.6 and a standard deviation (SD) of 0.87) are first to third-year students of Taras Shevchenko National University of Kyiv (Educational and Scientific Center "Institute of Biology and Medicine" and Faculty of Psychology). Participants were eligible to enroll in the study if they had normal vision or correction to normal, normal color vision, and no clinical or manifestations of mental or verbal, or nonverbal learning disabilities. Exclusion criteria were the use of psychotropic drugs, drug or alcohol addiction, and psychiatric or neurological complaints. Table 1 shows the details of the data used in the article.

Experiments

Arithmetic tasks in this study involve the serial subtraction of two numbers. Each test session begins with the verbal communication of 4-digit numbers (minimum) and 2-digit numbers (subsets) (for example, 4753 and 17, 3141 and 42, etc.). If the calculation for a particular subject was incorrect, the corresponding value is not an integer. Mental arithmetic performance is considered a standardized stress-inducing experimental protocol. Serial subtraction during 15 min is considered to be psychosocial stress (28).

During the EEG recording, participants sat in a dark, soundproof enclosure and slept comfortably in a comfortable chair. Before the experiment, participants were instructed to relax at-rest state and were given information about arithmetic tasks. Participants count accurately and quickly to the rhythm they set without any conversation or use of nervous movements. After three minutes of adaptation to the experimental conditions, EEG recording was performed at rest state with closed eyes (over the next three minutes). Participants then performed a mental arithmetic work of subtraction serial for 4 minutes.

In this study, we collected and stored EEG recordings in the last three minutes of the rest period and the first minute of the mental arithmetic performance. These periods have been selected since the task performance strategy is formed at the same time as the task is performed and the participants' emotional state changes significantly due to mental overload. Increasing the numbers provided is used to check the difficulty of the task (29). The difficulty of individual work for participants can be assessed by the number of operations performed per unit time and according to the characteristics of the proposed numbers. In this work, we used a set of

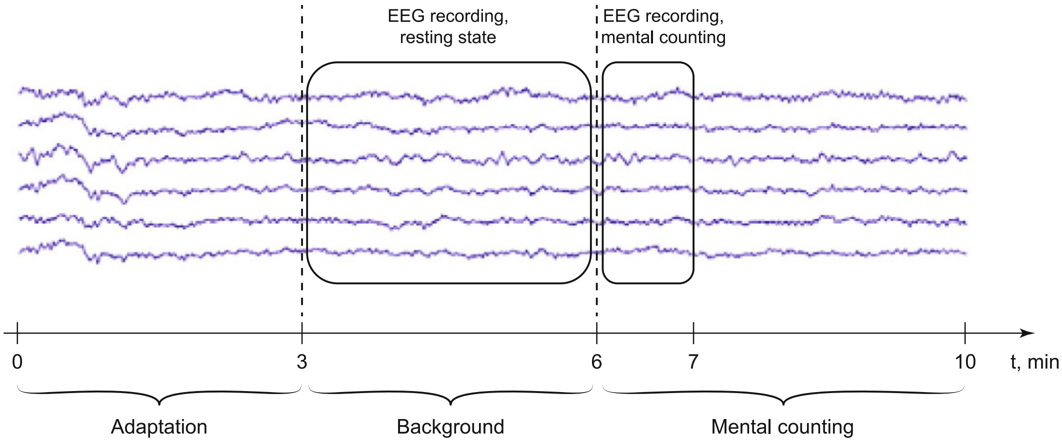

Fig. 1. Different brain states in general (27).

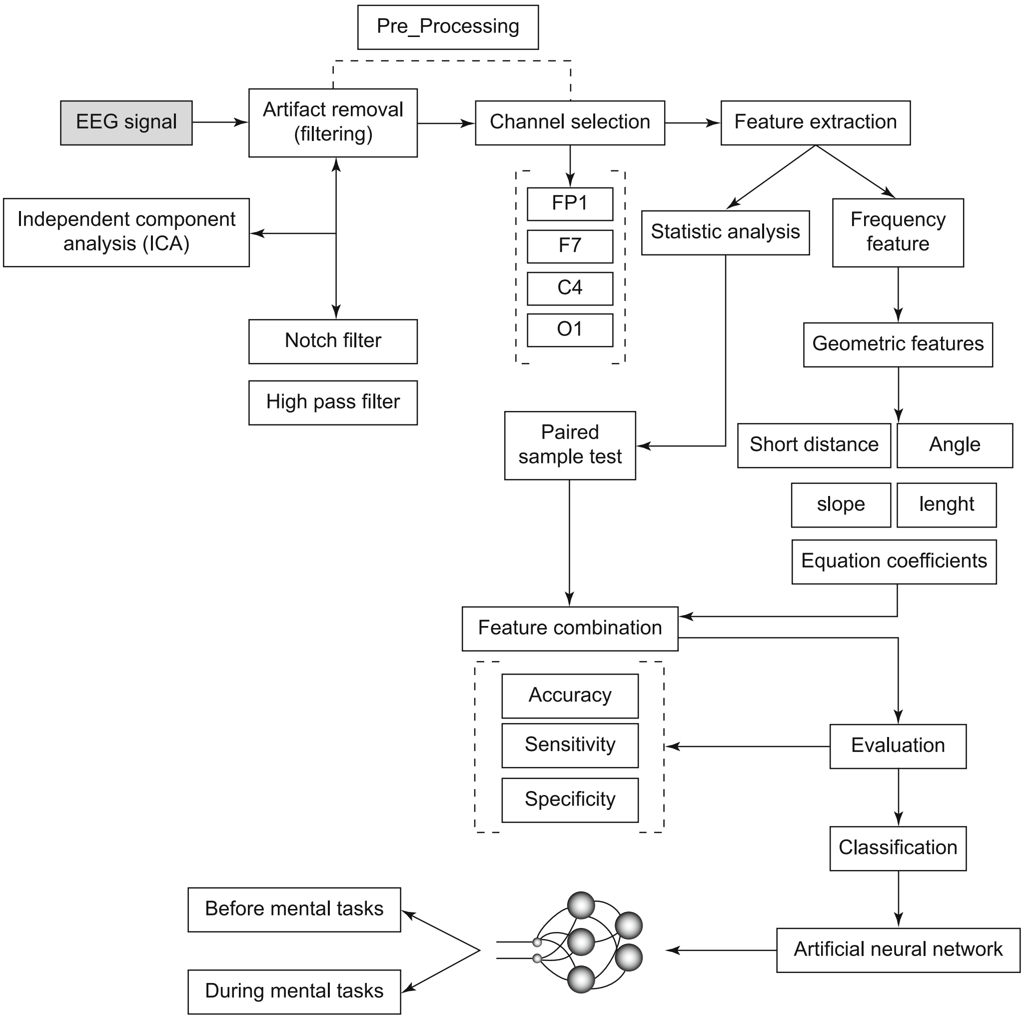

Fig. 2. The block diagram.

changes (ranked series) of behavior data as a basis for grouping to identify the EEG characteristics associated with difficulty for participants. Based on the number of account operations per minute, we divided the sample (36 people) into two groups: The proposed work was difficult for a group of participants, and people performed poor mental calculations with the number of calculations every four minutes as 3.6±7 (Group "B", 12 people, operation number=7, standard deviation SD=3.6), The second group of people performed good quality mathematical calculations with the number of calculations every four minutes as 21±7.4 (Group "G", 24 people, operation number=21, SD=7.4). Figure 1 shows the test process. In Figure 2, we have a block diagram of our proposed algorithm.

Processing

Artifact Removal

EEGs were recorded using Neurocom's 23-channel unipolar EEG system. (Ukraine, XAI-) MEDICA silver chloride/silver electrodes were placed symmetrically on the anterior floor skin. Front (Fp1, Fp2), Front (F8, F7, F, F4, F3), Central (Cz, C4, C3), Parietal (Pz, P4, P3), occipital (O2, O1), Temporal (T6, T5, T4, T3), sites were recorded in accordance with International 10/20 scheme. All electrodes were referred to as interconnected ear reference electrodes. The impedance between the electrodes was less than 5 k/ohm. The sample rate was 500 Hz per channel. Data were processed using MATLAB software version 2020. First, to remove the existing noise and artifacts, a high-pass filter with a cut-off frequency of 0.5 Hz, a low-pass filter with a cut-off frequency of 45 Hz, and a power line notch filter (50 Hz) was used.

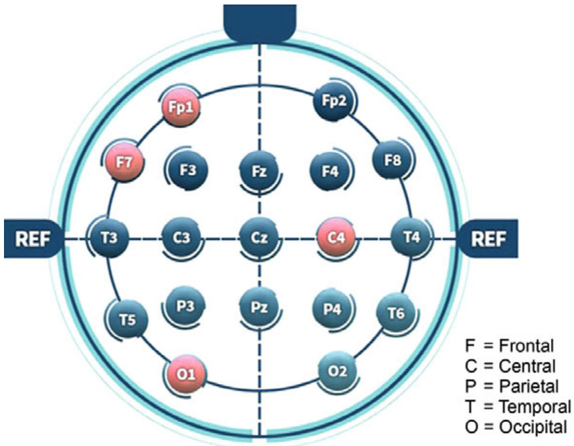

Fig.3. Position of 23 EEG channels.

Channel selection

Channel selection before feature extraction can reduce computational complexity, the amount of overfitting, dimensions, and setup time. It is also possible to find the optimal channel with the help of this selection and improve the performance of the model.

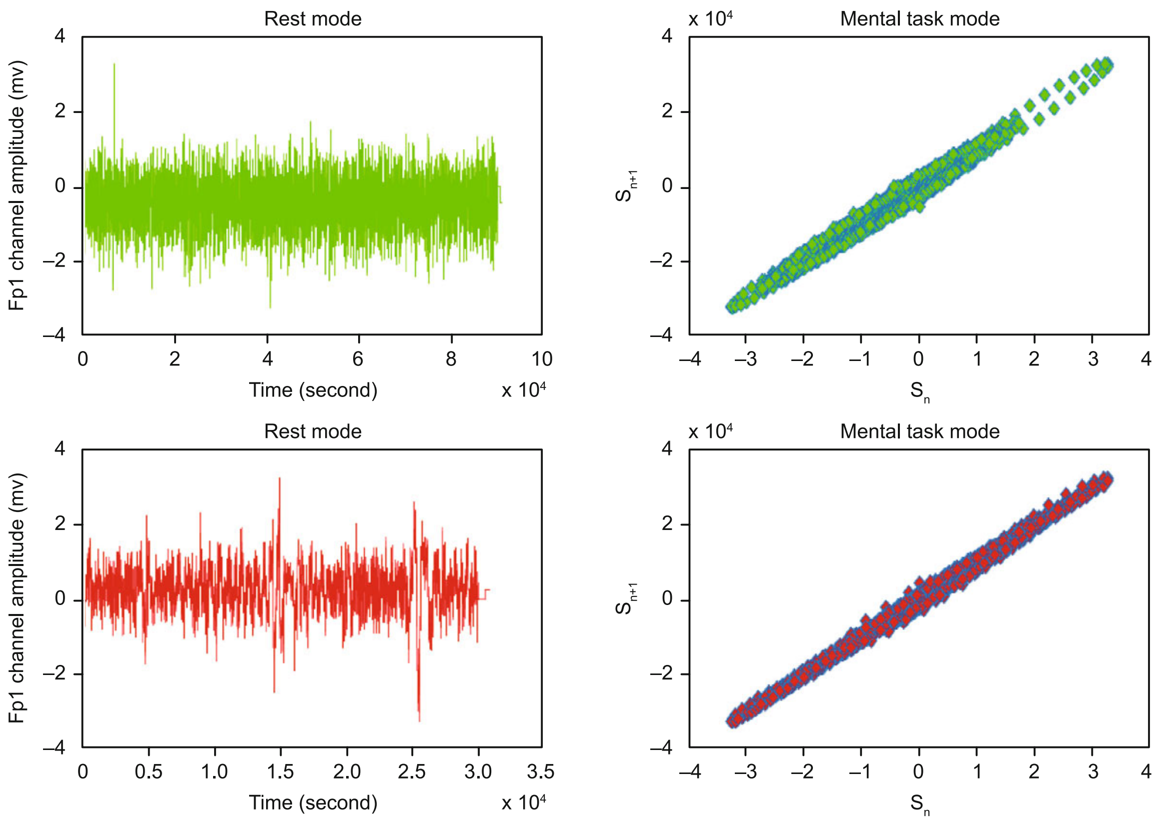

Fig. 4. Signal processing of the first sample in the Fp1 channel.

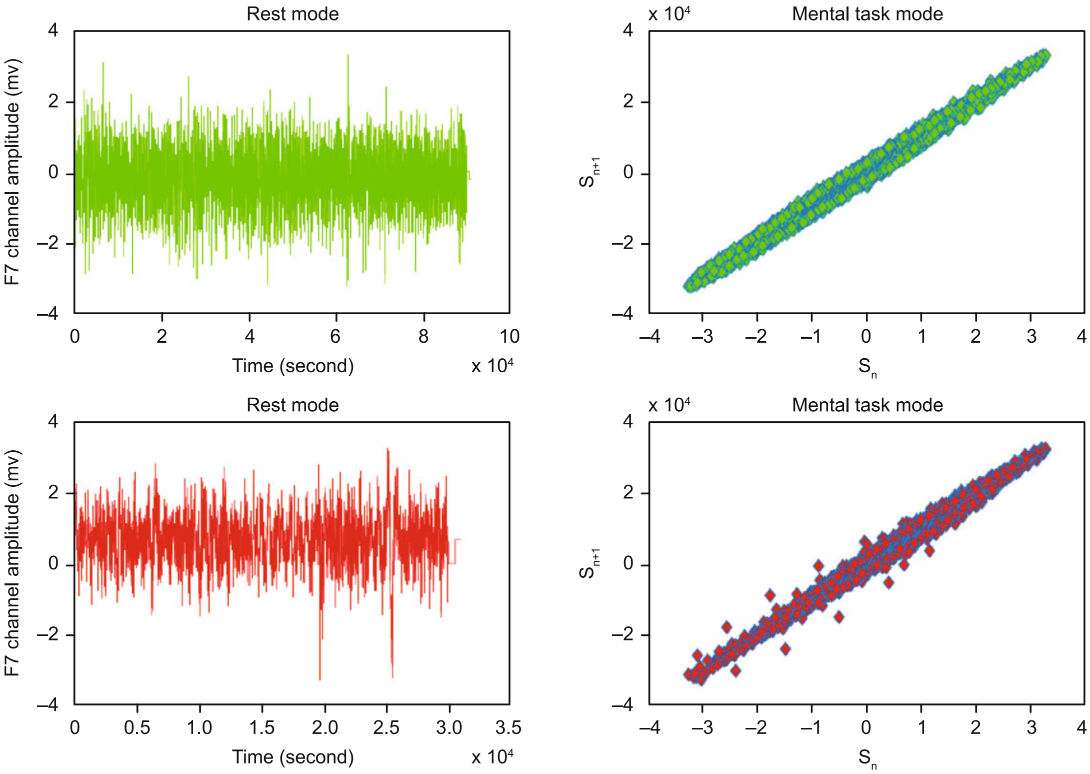

Fig. 5. Signal processing of the first sample in the F7 channel.

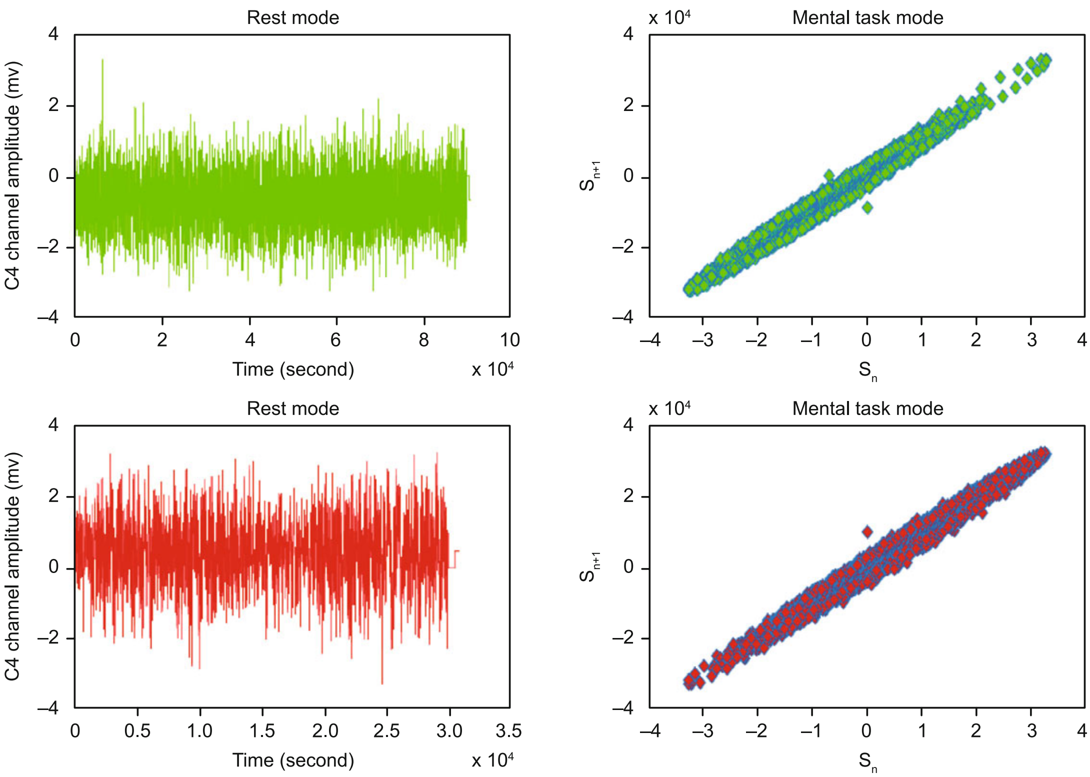

Fig. 6. Signal processing of the first sample in the C4 channel.

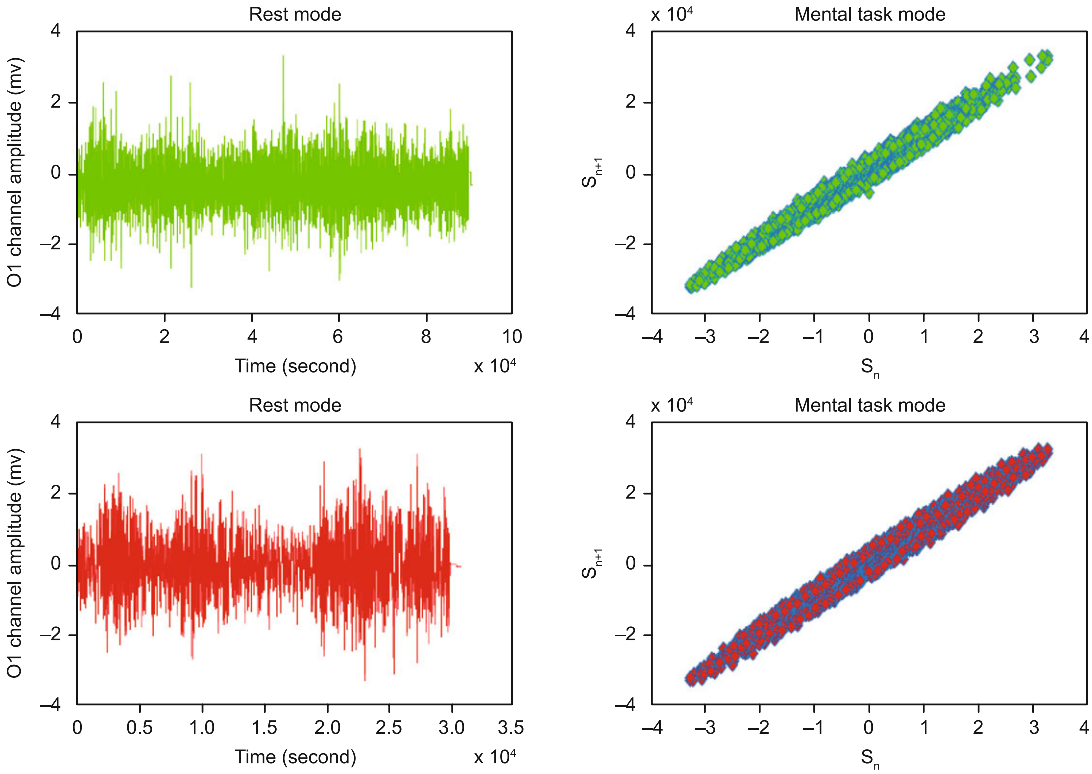

Fig. 7. Signal processing of the first sample in the O1 channel.

We derive the features according to the focus of the EEG signal compared to the rest mode and during mental calculations with approximation entropy, dispersion entropy, sample entropy, and slope entropy features and having p values less than 0.05 obtained from the previous results, and used 4 channels (Fp1, F7, C4, O1) to extract the features and classify it. Graphic mapping when performing arithmetic tasks indicated the greater activity of the frontal canals in the left and center-right and the occipital region, and the ears are the reference. Other common functions, such as arithmetic, voice recognition, and emotion, are more bilaterally managed, and capturing these signals from the head more accurately represents the areas of the brain involved. Figure 3 shows how the electrodes are displayed according to standard 20–10.

Feature extraction

An important step in processing EEG signal data is the feature extraction step. Due to the fact that the information in the EEG signals in the time domain is not accurately recognizable, frequency domain features have been used, which are among the features that have shown relatively good performance in the processing of various brain signals. Another approach to extract features from the EEG signal is to use nonlinear features. The nature of EEG signals is nonlinear, so the use of nonlinear features best explores the information contained in the signal. Nonlinear features can describe the processes produced in the biological system in more efficient ways. Parameters that express chaotic behavior are divided into two categories. The first set of parameters describes how the system behaves over time, such as the Lyapunov exponent and the second category emphasizes the geometric nature of motion paths in space, such as the fractal dimension. All calculations are performed using MATLAB software and without using the program's advanced toolbox. This reduces the time required to process the data. In this paper, a proposed nonlinear method is developed that applies directly to the data. Initially, the signal is transmitted from the time domain to the phase point, where a more accurate and complete description of brain dynamics is obtained.

Figure 4 shows the EEG signal in the FP1 channel over the entire period in both rest and mental work. Figure 5 shows the EEG signal in the F7 channel over the entire period in both rest and mental work modes. Figure 6 shows the EEG signal in the C4 channel over the entire period in both rest and mental work. Figure 7 shows the EEG signal in the O1 channel over the entire period in both rest and mental work.

The Poincare diagram and its large diameter and small diameter are known as criteria for short-term changes in EEG signals (30). We calculated the features of each signal after preprocessing and filtration using Poincare diagrams. Poincare diagram is a two-dimensional scatter plot diagram made of consecutive data points in a given time series S_1, S_2, …, S_n on the axis (X: S_n, Y: S_{n+1}) on the cartesian plane. This diagram shows the S_n time series in phase space or cartesian plane. Doing so defines a criterion for selecting delays based on auto-correlation performance. To extract the features, we need two descriptors, short-term and long-term, called SD. The two short-term and long-term descriptors are SD_1 and SD_2, representing the partial axis and the principal axis of the elliptical diagram (31). The line of identity is a 45-degree imaginary diagonal line in the Poincare design (32) and the points on the imaginary line have the attribute $S_n = S_{n+1}$. SD_1 measures the scatter of points perpendicular to the identity line, while SD_2 measures the scatter along the identity line. Equation (1) shows the parameters of the Poincare diagram.

$$SD_1{}^2 = \tfrac{1}{2} SDSD^2 = \gamma S_n(0) - \gamma S_n$$
$$SD_2{}^2 = 2SDS_n{}^2 - \tfrac{1}{2} SDSD^2 = \gamma S_n(0) - \gamma S_{n(1)} - 2\overline{Sn^2} \quad (1)$$

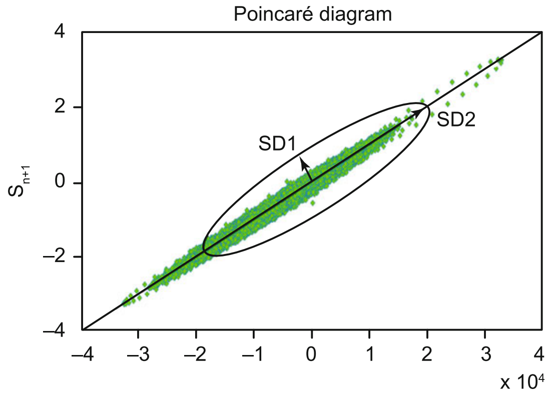

Fig. 8. Shows the Poincaré diagram.

Poincare diagram analysis is mainly linear statistics. Therefore, there are limitations in extracting all physiological mechanisms in a time series. We created a new form of mapping to distinguish between rest mode and mental calculations, which has been very useful for our study. This new mapping is based on Poincare diagram points according to the Sn average at time series intervals. By analyzing the distribution of points, we were able to classify the triangle in Figure 8 by extracting geometric features such as sides, shortest median lengths, and angles. Figure 9 shows the distribution points in TRM for mental task and rest modes. Figure 10 shows geometric features in two modes.

Figure 4 to7 shows the distribution of points in Triangular Return Mapping (TRM) for rest and mental work modes. The first feature of the sides of the triangle was Figure 9, in that Equation (2) shows the distance between vertices.

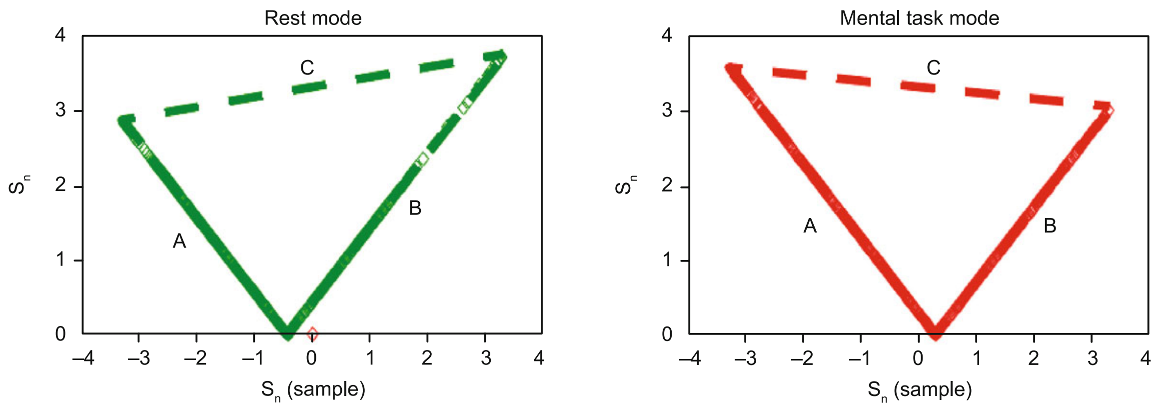

Fig. 9. Distribute points in TRM for mental task and rest mode.

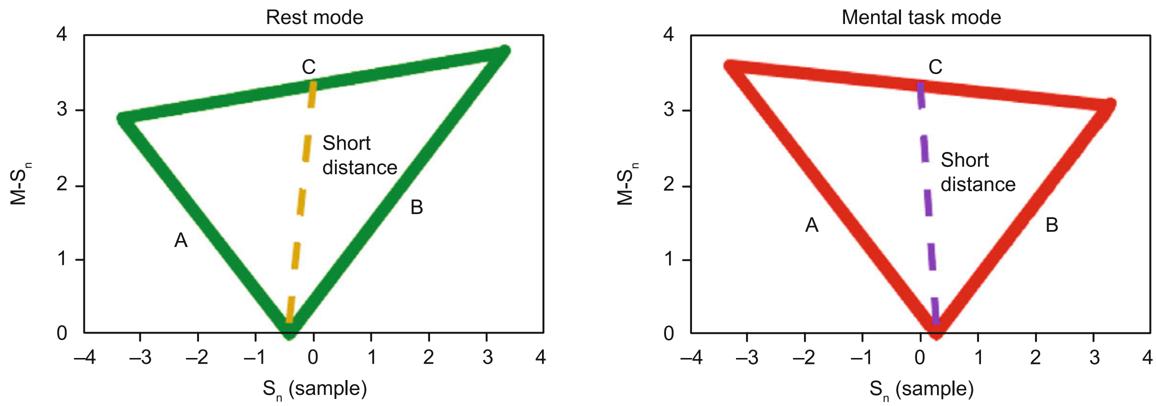

Fig. 10. Geometric features include the length of the shortest median length and angle of the sides.

$$\sqrt{((X(2)-X(1))^2+((Y(2)-Y(1))^2}$$
$$\sqrt{((X(4)-X(3))^2+((Y(3))^2} \qquad (2)$$
$$\sqrt{((X(6)-\mathrm{X}(5))^2+((Y(6)-Y(5))^2}$$

After extracting the sides, due to the possibility of the same triangles drawn in two different states and no differentiation, as well as to achieve more features that have information contained in the signal, other methods of feature extraction were investigated. We obtained the angles and the distance of the shortest side from the vertex of the triangle as other features with Figures 11 and 12. Figure 11shows the properties of angles in a triangle. Figure12 shows the shortest line segment from the vertex of the triangle to the middle of the other two sides

In the next step, to achieve better differentiation, we created another form of new phase space. Given that all the extracted features are put together in one feature vector, the fact that one feature is too large can overshadow the effect of the small features, due to the range of numbers, the new shape, which was different from other shapes in terms of dimension and dynamic range, the normalization method was used to limit the range values.

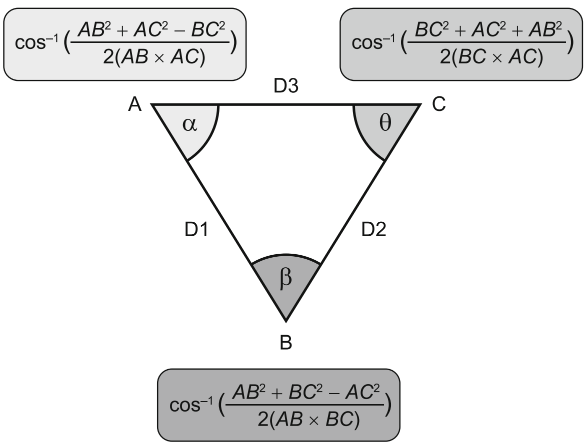

Fig. 11. the properties of angles in a triangle.

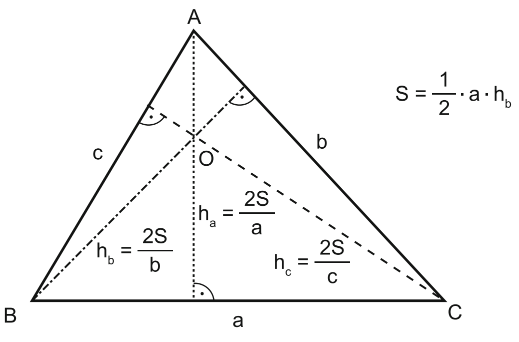

Fig. 12. The shortest line segment from the vertex of the triangle to the middle of the other two sides.

Tab. 2. Recognize the differentiation of selected features.

p	FP1	F7	C4	O1
D1	0.051	0.17	0.026	2.8×10^{-3}
D2	0.046	0.46	0.029	3.8×10^{-3}
D3	0.061	0.46	0.9	0.48
α	0.62	0.046	0.028	5.6×10^{-3}
β	0.42	0.05	0.028	4.1e-3
γ	0.84	0.78	0.23	0.31
D(S)	0.036	0.63	0.79	0.82
P1	2.6×10^{-4}	0.81	1.1×10^{-6}	0.053
P2	0.011	0.12	0.038	0.019
P3	0.56	9.2×10^{-3}	0.32	0.88
P4	0.053	0.14	0.021	1.4×10^{-4}
H	0.38	0.39	0.19	0.043

Tab. 3. The most meaningful features.

Channel	Feature
FP1	D1 D2 D3 D(S) P1 P2 P4
F7	P3
C4	D1 D2 P1 P2 P4
O1	D1 D2 P1 P2 P4 H

Min-mix normalization is at least one method of data normalization in which it can specifically normalize data within a predetermined boundary (33).

According to the normalization technique, we will have a general formula for minimum and maximum (1,0) in the form of Equation (3). (Normalize the general formula)

$$\mathrm{i}' = \frac{i-\min(i)}{\max(i)-\min(i)} \qquad (3)$$

max: Maximum signal value
min: Minimum signal value
i': The normalized value of the signal

We normalized the signals by changing the range with the desired value (-1,1) for optimal system performance. Equation (4) shows the re-change of the range between an arbitrary set of values (c, d).

$$\mathrm{i}' = c \ \frac{(i-\min(x))(d-c)}{\max(i)-\min(i)} \qquad (4)$$

To extract the feature from Figure 13 after achieving the third-degree equation of each signal according to Equation 4, we calculated the coefficients of the equations (p1, p2, p3, p4) and also calculated the slope from the point max to the point min of the diagram according to Equation (4). Equation (5) shows the coefficients of the third-degree equation in Figure 13. Equation (6) shows the slope from the max to min diagram. Figure 13 shows the new phase space of the normalized data

$$\mathrm{F(x)} = \mathrm{p_1x^3 + p_2x^2 + p_3x + p_4} \qquad (5)$$

$$\mathrm{m} = \frac{\mathrm{Y(2)-Y(1)}}{\mathrm{X(2)-X(1)}} \qquad (6)$$

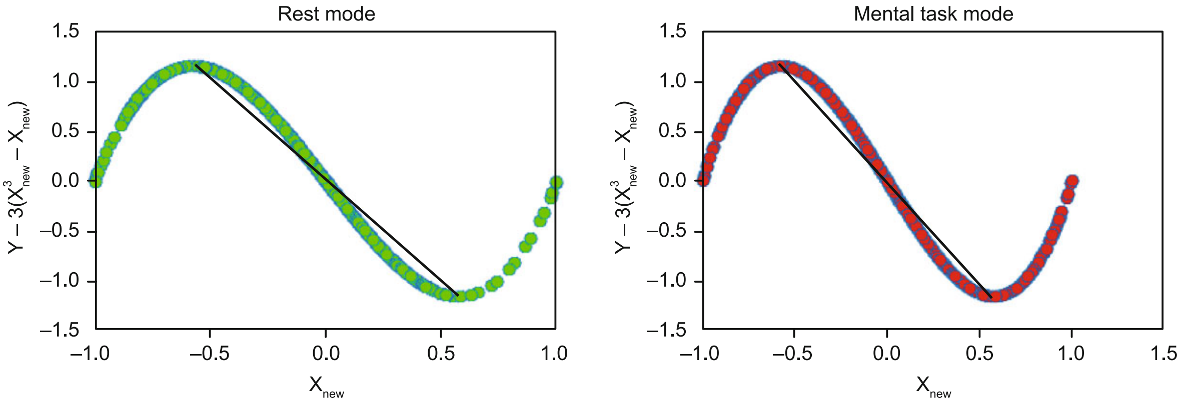

Fig. 13. New map of 3rd degree normalized data for two rest modes and first-person mental Task in Fp1 channel.

Classification

It is always important to choose the best method for selecting features and classifications. To classify the features extracted from the EEG signal, four functional classifications are the artificial neural network, the decision tree, the Gaussian Naive Bayes category, and the support vector machines. The feature vector of the selected channels uses the classifier structure such as ANN and also a network is designed with the feature vector of 36 inputs of each topic. The standard neural network classified for this task has a leading layer, a hidden layer, and an output layer, which is trained by an error propagation algorithm.

In this structure, according to the example, the input vector is applied to the input layer, so that all inputs are distributed to each unit. Then in the first hidden layer, all units have weight vectors that are multiplied by these input vectors and each unit adds these inputs and converts them to a value by the TANSIG activation function. Then, by multiplying the output vector by the weights from the hidden layer, after summing and activating it in these units, we reach the real output of the network. Network training was performed to minimize the error by setting all weights to small and random values as well as a random selection of the number of layers. Figure 14 shows the structure of an ANN.

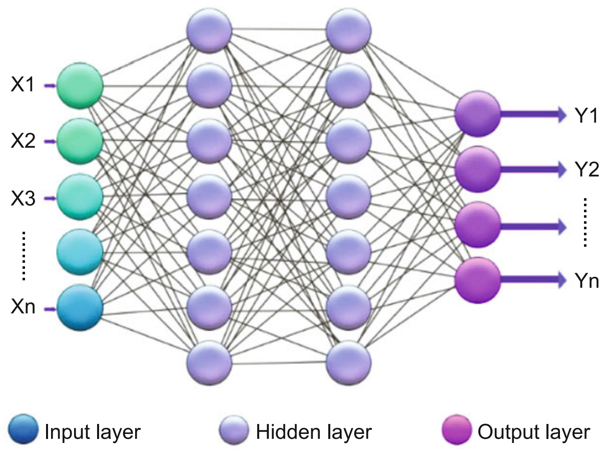

Fig. 14. Structure of Artificial neural network.

Statistical analysis

Finally, channel analysis (FP1, F7, C4, O'1) was performed using the fast Fourier transform algorithmic technique, and finally, this information was quantitatively entered into MATLAB software, and using the Paired Sample Test, the necessary comparison was made to determine the differences between the brain in the state of mental calculations and the rest mode. An index called p or significant level has been used to confirm the accuracy of the selected features and differentiation. According to Table 2, to better distinguish differentiation, if it is $p < 0.05$ for each feature, the selected features are approved. Table 2 shows that not all features in the selected channels are well differentiated.

To compare the data at rest and mental calculation in 4 channels, it is observed that the variables D1, D2, P1, P2, P4 in the three channels FP1, C4, and O1 with $p < 0.05$ have a significant level, while in F7 channel, none of these variables have a significant level. Also, the variable H has a significant level only in the o1 channel. Table 3 shows the variables of each channel that have a significant level:

Feature combination

In this section, after finding the variables of each channel and calculating their degree of differentiation, we combined the channels and examined them in 15 possible ways.

Single channel: FP1, F7, C4, O1

Dual composition: FP1 F7, FP1 C4, FP1 O1, F7 C4, F7 O1, C4 O1

Triple Composition: FP1 F7 C4, FP1 F7 O1, FP1 C4 O1, F7 C4 O1

Fourth Composition: FP1 F7 C4 O1

Various channel features, which may be referred to as the combined feature/channel selection, increase the search space, because in the case of the maximum possible combination of channels (combination of 4) there are 20 variables, while in the case of single-channel there are 5 variables.

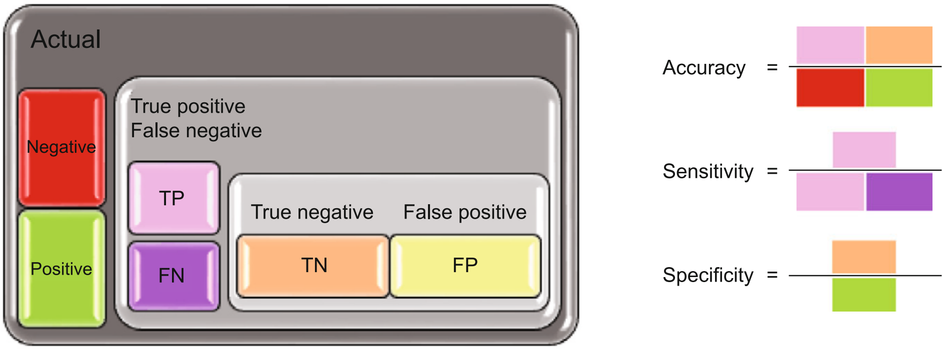

Fig. 15. Evaluation criteria.

Results

Performance evaluation of the proposed algorithm

In this paper, we evaluated the channels individually and in combination, with 3 criteria of accuracy, sensitivity, and specificity. Figure 15 shows the proposed evaluation criteria.

People who were in a state of mental arithmetic were considered healthy and those who were at rest were considered sick. In the evaluation criterion when the person is healthy, while the system has not correctly diagnosed (FP) and when it correctly diagnoses (TN). In addition, when a person is ill, while his illness is not correctly diagnosed (FN) and if diagnosed correctly (TP).

Table 4 shows the performance evaluation of the proposed algorithm (accuracy, sensitivity, specificity) for all the obtained properties.

In the studies performed according to Table 4, it was observed that in the combination of FP1 and F7 channels, we reached the lowest error (7.007×10–7), and also in the criteria of accuracy, sensitivity, and specificity, we achieved 100 %, but in other cases, we encountered different error rates. In the next step, for more communication between channels and the effect of the degree of differentiation of their features, combine only those features approved in Table 4 and design different neural network structures for achieving the desired output and the least amount of error. We obtained the results of Table 5, which shows the performance evaluation of the proposed algorithm (accuracy, sensitivity, specificity) for the distinctive features obtained.

Tab. 4. Performance evaluation of the proposed algorithm.

Channels	Error	Accuracy	Sensitivity	Specificity
Fp1	1.1	98.6%	100%	97%
F7	1.4	98.6%	97%	100%
C4	4.4	94.4%	94.4%	94.4%
O1	15.0	84.7%	88.8%	80.5%
Fp1, F7	7.0×10^{-7}	100%	100%	100%
Fp1, c4	5.1	91.6%	91.6%	91.6%
Fp1, o1	9.8	87.5%	84.7%	90.2%
F7, c4	13.0	84%	87.5%	80.5%
F7, o1	19.0	72.2%	91.6%	52.7%
C4, o1	14.0	80.5%	83.3%	77.7%
Fp1, f7, c4	7.1	90.7%	97.2%	84.2%
Fp1, f7, o1	8.2	90.2%	95.3%	85.1%
Fp1, c4, o1	12.0	82.8%	84.2%	81.4%
F7, c4, o1	15.0	82.8%	97.2%	68.5%
Fp1, f7, c4, o1	9.9	86.1%	90.9%	81.2%

Tab. 5. Optimal output in different neural network structures.

Channels	Error	Accuracy	Sensitivity	Specificity
FP1	3.8	95.8%	94.4%	97.2%
F7	6.2×10^{-7}	100%	100%	100%
C4	1.4×10^{-7}	100%	100%	100%
O1	14.0	80%	86.1%	75%
Fp1, F7	1.3×10^{-7}	100%	100%	100%
Fp1, C4	3.9×10^{-7}	100%	100%	100%
Fp1, O1	7.9	93%	94.4%	91.6%
F7, C4	1.2×10^{-7}	100%	100%	100%
F7, O1	2.8×10^{-7}	100%	100%	100%
C4, O1	4.6	95.8%	97.2%	94.4%
Fp1, F7, C4	5.1×10^{-7}	100%	100%	100%
Fp1, F7, O1	1.6×10^{-7}	100%	100%	100%
Fp1, C4, O1	0.12	100%	100%	100%
F7, C4, O1	1.5×10^{-7}	100%	100%	100%
Fp1, F7, C4, O1	9.9×10^{-8}	100%	100%	100%

For this purpose, properties for each channel were calculated from the EEG signal and then, due to the large dimensions of the feature space, the p algorithm was used to select the optimal features in each channel. One group of features had the highest value in the mental calculation mode and the other group had the highest value in the rest mode. We also combined the selected channels with the features obtained from each channel. The results show that by using the distinctive features in each channel combination mode, we achieve 100 % accuracy, 100 % sensitivity, and 100 % specificity.

Discussion

In this paper, a new, simple, and low-cost method based on an intelligent algorithm through EEG signal extraction using geometric features is proposed to increase the accuracy of rest mode classification and mental tasks. The data set used by the brain signals at rest and in mental tasks is obtained from PhysioNet.

Tab. 6. Comparison of recent studies on EEG individuals during mental arithmetic tasks.

No	Authors	Years	Methods	Results
1	Guilherme A. Barreto et al (34)	2004	SOM, MLP, QGC	Accuracy: (73%_100%)
2	NAN-Yingliang et al (35)	2006	ELM, BPNN, SVM	SVM is better
3	Saurabh Kumar Agarwal et al (36)	2015	BSANN	Accuracy:68.56%
4	M. Serdar Bascil et al (37)	2016	LS-SVM, LVQ, MLNN, PNN	average accuracy:92.27%
5	Kusuma Mohan Chandra et al (38)	2015	SVM, k-NN	Accuracy by k_NN:92%, Specificity:95%, Sensitivity:80%, Accuracy by SVM:98% The accuracy is ranging between 50% to 98% on per subject per task basis and on different methods
6	Ivaylo Ivaylov et al (39)	2020	LDA, Linear SVM, RBF-Kernel SVM, Decision Tree, ANN, Logistic Regression	RBF-Kernel based SVM is the best performing standard classifier on the experimental
7	Suman Dutta et al (40)	2018	LS_SVM	Accuracy:77.77%
8	Suman Dutta et al (41)	2018	LS_SVM	Accuracy:83.33% Specificity:100%
9	DebashisDas Chakladar et al (42)	2020	GWO, deep BLSTM-LSTM	86.33% and 82.57% classification accuracy for “No task” and “SIMKAP-based multitasking activity
10	M.Hariharan et al (43)	2014	LDA, KNN, SVM, Stock well transform (ST)	Accuracy: between 84.72% and 98.95%
11	DebatriChatterjee et al (44)	2021	naive Bayes classifiers	Accuracy:85%
12	Cigdem InanAci et al (45)	2019	SVM, kNN and ANFIS	Accuracy by SVM: 96.70%

Comparison of the results of this paper with previous results of studies showed better performance of the proposed method in distinguishing between two modes of mental task and rest. Our approach is a new nonlinear representation that can form various geometric shapes in phase space. In the method of recursive mapping of EEG signals, we transformed the individuals into a different phase from the nonlinear methods used, and we also designed the Poincaré diagram to extract the features to a new phase. Extraction of features from geometric shapes will be for better distinction between two modes (mental task and rest). Extracted distinctive features such as sides of triangles, angles, distance from the shortest height to the side of the triangle, equations of the third degree, and slope were calculated. Also, the spaces used in this study were TRM design, Poincare diagram, and ANN. Table 6 shows summarize the results of research conducted in this field.

This paper deals with a new automated approach based on ANN and TRM structuring methods to differentiate mental arithmetic tasks including subtraction versus rest mode in 4 channels of high precision EEG signals on 36 participants. The high accuracy of the classification indicates that the method described in the future will be used to control, treat and diagnose patients who have lost an area of their brain due to various factors and children who have problems, in people with hyperactivity or mental activity. Disruptive is useful. In this study, the method described in the future is very useful for predicting and diagnosing the disease of people in different fields and increasing the ability of the brain to achieve the desired learning time in people. Linear analysis with a combination of features was selected as the top classification in terms of processing time

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