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Analysis of working memory from EEG signals under different emotional states

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ABSTRACT

This study analyzes electroencephalography (EEG) measurements during short-term memory retention under different emotional states. A public-domain library with emotion-annotated images (IAPS) was used to stimulate neutral, negative, and positive emotions. The associated EEG data were acquired from twelve volunteers (between 20 and 26 years old; ten males and two females). Each participant was exposed to three sessions back-to-back on the same day. Each session corresponded to the induced emotional states (positive, negative and neutral) and consisted of relaxation, memorization of a list of ten words and ten numbers, watching a set of images to arouse emotion, and recalling the words and numbers memorized earlier. Statistical and spectral features of EEG data were analyzed for two instances: emotion recognition (neutral, negative, and positive) and recall events under the three emotional states. By designing two baseline machine-learning models, support vector machines (SVMs) and K-nearest neighbor (KNN), the significance of the EEG bands and the brain lobes were studied. Experimental results suggest that the short-term (working) memory recalls after exposure to neutral, negative, and positive images (to arouse neutral, negative, and positive emotions) differ from each other significantly (at alpha level 0.001). We have found that each EEG band carries unique information in both emotion and memory recall classification tasks and recommend that the entire EEG signal frequency range must be analyzed in future similar studies. On the other hand, we also have found that each brain region carries similar information as it relates to each task (i.e., memorization, recall), thus only one of the brain regions can be analyzed in future studies in order to avoid complexity and high computation time.

1. Introduction

Studies conducted by utilizing peripheral signals and the combination of peripheral and electroencephalography (EEG) signals, reported that electrical potentials measured using electrodes on the scalp provided rich data related to brain activity. Processing of these signals would permit to gather data about mental activity and emotional state. EEG has been used in a variety of applications. Its clinical applications include investigation of sleep stages [19], mental and brain disorders [41,1], autism [37], and Alzheimer's disease [59]. Memory, cognition, mental effort detection, attention monitoring, and learning have also been studied during the last couple of decades [58,21,55]. Additionally, classification of emotional states has been studied widely by using EEG signals [61,3]. Brain-computer interface (BCI) is another field that employs EEG signals to classify mental tasks and to control brain activity [38].

Merriam dictionary defines emotion as an affective aspect of consciousness and it influences one's decision-making, consciousness, reasoning, attention, memory retention and learning. Anger, sadness, and joy are the commonly studied emotional states in most studies that use facial images and speech signals to recognize the emotional state of a person. However, their interpretation is not always objective. EEG signals may contain more sensitive and accurate information than facial expressions and speech signals. One can look or sound happy while sad or vice versa. On the other hand, EEG signals may capture one's true emotional state regardless how individuals look or sound. Advanced Human-computer Interface (HCI) Brain-computer Interface (BCI) technologies recognize the importance of affective communication and begin to include it in the design of new systems [24]. Neuroscientists and educators have been long investigating the role of emotions in the process of learning. For example, several studies in neuro-physiology, psychology, and BCI report that emotions affect cognitive and learning

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processes [42]. The influence of neutral, negative, and positive emotional states on short-term memory have been studied for the first time by using EEG measurements [6]. The study used average short-time energy to compare the brain activity during memorization of numbers and words under various emotional events. Higher average short-time energy was reported during the memorization of words.

It has been long assumed that the emotional aspects of human behavior are separate from the more rational aspects of thought. Early perspectives viewed emotions as being processed in the limbic system (e. g., the hippocampus, amygdala), separate from the neo-cortex, where cognitive and learning capacities are processed. Recent research in neuroscience and cognitive sciences shows a connection between the two structures. These studies indicate that emotions may modulate a variety of cognitive processes, including perception, memory, attention, and reasoning [9,16,18,27,32]. Structures that are considered parts of the limbic system have been shown to have an active involvement in cognitive processes, such as memory, while structures responsible for cognitive functions, such as the pre-frontal cortex, have been shown to play an active role in processing information related to emotion [18]. Hadley et al. [22] studied the connection between emotion and short-term memory. Their results stated that taboo superiority in short-term recall reflects context-specific required processes, instead of emotion related differences in rehearsal, processing time, output interference, time-based decay, or guessing biases. Additionally, Pessoa [43] showed that individuals with damage to parts of the brain that process emotional information, show impaired learning and decision making, despite maintaining intact those part of the brain (i.e., neocortex) responsible for reasoning, memory and attention.

Nowadays, the process of learning takes place in the brain and involves either direct communication among people or communication mediated by the computer. According to the cognitive learning theory, the process of learning can be explained by analyzing the mental processes that occur in the brain, as they are influenced by intrinsic (e.g., mood) and extrinsic factors (e.g., emotional stimuli). Previous studies reported that learning in both the traditional setting and the computer-mediated environment can be influenced by emotions [14,31]. On the other hand, the cognitive load theory [40,53,54] explains learning as consisting of the mental processes that balance working memory (WM) and long-term-memory (LTM) while dealing with novel information. The main goal of cognitive learning theory is to explain how efficient learning of complex tasks is accomplished by using the relationship between the limited WM and unlimited LTM. To achieve optimum learning, educators who rely on findings extracted from neuroscience research, will attempt to engineer instructional control of cognitive load by designing teaching methods that substitute productive for unproductive WM load. Many aspects related to the physical learning environment were shown to have an impact on WM and consequently, on learning: learning task specificity [39], task redundancy [34], attention [25], and a combination of learning tasks and learner characteristics [26]. More recently, it has been suggested [20] that WM capacity that is available for learning is not only determined by task and learner characteristics, but it also depends on aspects of the physical environment and affective factors (e.g., emotion). Emotion plays an important role in memory function and, implicitly, in learning. For example, emotions associated with certain events can enhance memory for some details of the event [27], while emotions elicited during an emotional event have been shown to impair the recall of previously learned information [30]. In addition, emotions can influence which information is attended to or retrieved from memory [32,35,36,46]. A very recent study conducted by Zhang et al. [60] reported that effects of emotion on short-term memory are also dependent on its capacity: Both negative and positive emotions enhanced working memory in individuals with a high memory capacity, and impaired it in individuals with low memory capacity.

Badara et al. [6] presented promising findings that connected emotion, learning, and event-related potentials (ERP) measured in the brain, by indicating that emotional states have an influence on memory and recall, and can be studied by examining brain activity, which can be measured through EEG signals. As brain activity related to an emotional stimulus should occur shortly after the stimulus' onset, brain activity measured through EEG can be useful for WM assessment, which is an important step in the process of learning.

Therefore, this study stimulated neutral, negative, and positive emotions by using IAPS images [29] and analyzed recall events after exposure to the IAPS images. The goal of our work was to explore the similarities and differences among EEG measurements collected during recall events. The main objective of the study was to explore whether different emotional states lead to statistical significant differences in EEG measurements in various brain lobes during elicitation of working memory. The paper is organized as follows: Section 2 includes experimental design, EEG acquisition procedure, and pre-processing procedures. Feature extraction and analysis are explained in the methodology section. Section 4 reports the experimental results. Discussions, reflections, and future works are presented in section 5.

2. Experimental design

2.1. Ethics statement

This research study was conducted with full compliance of research ethics norms, and more specifically the codes and practices established by the National Commission for the Protection of Human Subjects in Biomedical and Behavioral Research. The ethical aspects of this study were reviewed and approved by the Institutional Review Board. All study participants volunteered and provided written informed consent, while their anonymity has been preserved throughout the duration of the study and beyond its completion.

2.2. Study participants

Data were collected from twelve volunteers (between 20 and 26 years old; ten males and two females) after obtaining informed consent. Eleven participants were right-handed and one participant was left-handed. Because of technical reasons, the data collected from two participants (one female and one male) were removed from the study. In consequence, the study analyzed data from ten participants only. All participants had science and engineering education backgrounds and belonged to the same age group. They were all enrolled in a graduate level engineering program at the time of the study. Participants were recruited from a university located in Northeastern United States. Participants were compensated with an individual $15 gift card at the end of the experiment.

Participants completed two self-report measures. The first self-report measure was a questionnaire inquiring about their sleeping and eating habits, administered before the EEG data acquisition. Participants were eligible to take part in the study if they had minimum 8 h of sleep during the night before the experiment, did not have any brain injury or brain-related medical condition (i.e., epilepsy), and did not take any brain stimulant (i.e., drugs, caffeine, energy drinks, etc.) at least five hours before the EEG data acquisition. This measure was to prevent the inclusion in the study of any participant who either had a brain-related affliction or was exposed to substances that may interfere with the function of the brain. The second self-report measure was administered after the EEG data acquisition and represented an evaluation of emotion. The participants rated their emotion triggered by the neutral, negative, and positive images by using a five-point scale. This was done for the purpose of collecting self-assessments of emotional stimuli from participants. The approach was based on prior studies [13] that have shown that, for identical emotional stimuli, individual perception of emotion can strongly differ from the generally expected emotion, depending on the subject's past experiences.

2.3. Stimuli and software

A public-domain library with emotion-annotated images (IAPS) was used to stimulate neutral, negative, and positive emotions of participants. This database of visual emotional stimuli has been designed for the purpose of emotion elicitation and is accompanied by affective evaluations from experts or average judgments of several people [29]. Neutral pictures included landscapes and household objects; positive pictures included food items, children and happy families; negative pictures included snakes, mutilated bodies and scenes of attack and threat[1] . Every picture was presented on a 17-in computer monitor, situated approximately 50 cm from the participant, leading to an image presentation with a visible angle of 15 degrees horizontally and 11 degrees vertically. Each picture was presented for 3 s. The ANT Neuro system with 625 Hz sampling frequency was used for EEG measurements [49]. Non-magnetic and comfortable ANT WaveGuard caps were used, with a 32 Ag/AgCl sintered electrode configuration. Electrode caps were placed by the 10–20 electrode placement system.

2.4. Protocol

During the time of the event-related potential (ERP) acquisition by EEG, participants were asked to position themselves comfortably, so that postural muscle artifacts would be reduced. Each participant was exposed to three sessions back-to-back on the same day. Each session had four different scenarios, which consisted of: “class 1: relaxation (30 s)”, “class 2: memorization of a list of ten words and ten numbers (30 s)”, “class 3: watching a set of images (60 s)”, and “class 4: recalling the words and numbers memorized earlier (60 s)”. The word list contained ten words, with five words being event-related and five words being not event-related. Event-related words refer to words that were directly related to the type of image and the emotion triggered. For example, when participants were exposed to negative visual stimuli, such as images of mutilated individuals, the event-related words included the word ‘horror’. For positive visual stimuli, such as images of laughing babies, the event-related words included the word ‘caring’. The sessions exposed the participants to neutral, negative, and positive emotional stimuli elicited by a set of images, extracted from IAPS. Immediately after the exposure to each set of emotional stimuli, each participant was asked to recall and write down the words and numbers from the lists.

2.5. Self- assessment analysis

Elicitation of emotion has been shown to lead to changes in physiological, motor and behavioral components [50]. There is extensive literature on the assessment of emotion through the analysis of speech and facial expression, measurement of skin conductance responses, or monitoring of heart rate. It could be possible to consider these assessments for the detection of elicited emotion, after recording by adequate sensors and/or measurements. Nonetheless, we did not have access to such sensors and measurements and decided to rely on study participants’ perceptions of elicited emotion by the images included in IAPS.

According to the cognitive theory of emotions, emotions are elicited through a cognitive process called appraisal, which evaluates a stimulus according to certain criteria [17,51,50]. For this reason, an emotion evaluation step, corresponding to the appraisal process, was added after EEG data acquisition. Through this self-reported measure, participants rated their emotions triggered by the IAPS neutral, negative, and positive images by using a five-point scale. The chi-squared statistic (χ^2) was calculated to determine how much difference existed between observed rankings and rankings expected if there were no relationship at all between emotion and the ranking of triggered emotion (at $\alpha = 0.05$). For the ten participants included in the study, emotions elicited by neutral images were significantly ranked as ‘medium’ and emotions elicited by negative images were significantly ranked as ‘high’ ($\chi^2 = 8.333$, df = 3, $p < 0.05$). This indicates that neutral images did not elicit emotion, as expected, while negative images induced strong negative emotions in participants. Participants also indicated that positive images were not significantly associated with emotion ($\chi^2 = 2.111$, df = 3, $p > 0.05$).

2.6. Pre-Processing

The ANT Neuro system’s built-in artifact filtering was used to remove the eye movement. A notch filter was designed to remove the 60 Hz related to devices. EEG measurements of each channel were normalized by dividing the measurements by the maximum measurement value of the corresponding channel. The purpose of this normalization was to represent the EEG data in the range of [-1,1]. For a better fit, we normalized the feature set to have zero mean and unit variance. All signal processing was performed in the MATLAB software.

$$\mathrm{Normalized\_Data} = (\mathrm{Data} - \mathrm{Mean}\{\mathrm{Data}\})/\mathrm{Standard\_Deviation}\{\mathrm{Data}\} \quad (1)$$

```
% Notch filter design to remove 60 Hz
d = designfilt('bandstopiir','FilterOrder',2, ...
  'HalfPowerFrequency1',59,'HalfPowerFrequency2',61, ...
  'DesignMethod','butter','SampleRate',Fs);
buttLoop = filtfilt(d,filtered_signal);
```

A filter bank was designed to extract five main EEG bands: Delta band (1–3.9 Hz), theta band (4–7.9 Hz), Alpha band (8–12.9 Hz), Beta band (13–30 Hz), and Gamma band (30–100 Hz). The magnitude of responses of the designed filters are given in Fig. 1.

Delta band ranges up to 3.9 Hz, with the highest amplitude among the EEG bands. It is activated during sleep, attention, and mental task processing [23]. Theta band ranges from 4 to 7.9 Hz. The highest theta band power is related to a state of mind wandering [10], and neurological disorders [28]. Mind wandering is defined as a deficit in attention control and working memory. Alpha band ranges from 8 to 12.9 Hz. Relaxing activities increase the alpha waves. Klimesh [28] reported that alpha waves would be reduced when people open their eyes or process of mental tasks. Alpha frequency shows large inter-individual differences related to age and memory performance. Beta band ranges from 13 to 30 Hz, and is related to focus and thinking. Gamma band ranges above 30 Hz. Gamma band is associated with perception and cognition [33].

The layout of EEG electrodes on the cap is shown in Fig. 2. We used the following electrodes to represent the frontal, temporal, occipital, central, and parietal brain lobes. In this study, we analyzed the parietal and central lobes together.

Different brain lobes may be related to different functions of the brain. Representing more than third of the entire human hemisphere,

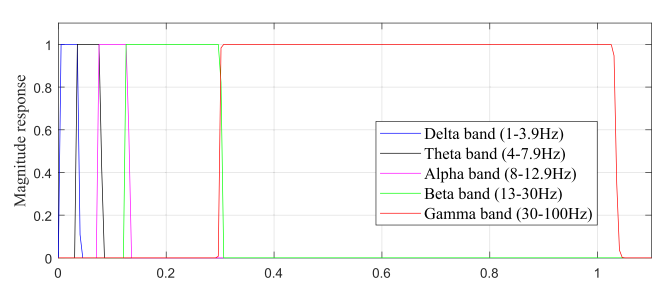

Fig. 1. Magnitude of responses of the designed filters for five EEG bands.

[1] The IAPS catalog numbers for pictures used in this study are: Neutral: 5720, 5725, 7035, 7042, 7057, 7547, 7490, 7545, 7041, 7700, 7500, 7180, 7175, 7090, 7080, 7050, 7030, 7020, 7010, 5500; Negative: 2205, 9050, 9075, 9220, 2688, 1300, 1120, 3100, 1070, 3000, 1050, 6370, 1090, 3350, 1930, 9040, 9490, 6260, 6510, 2345.1; Positive: 2345, 2332, 2530, 2216, 2091, 1600, 2050, 2070, 7405, 2311, 2340, 2341, 7200, 2347, 2208, 2224, 2306, 2374, 7350, 7330.

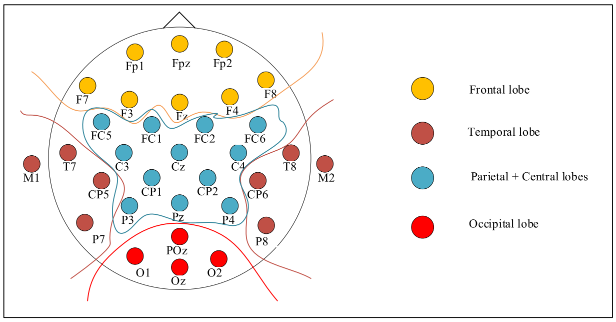

Fig. 2. The ANT neuro EEG cap layout for 32 electrodes according to the 10–20 electrode placement system. Electrodes FP1, FPz, FP2, F7, F3, FZ, F4, and F8 are used to represent the frontal lobe. The electrodes FC5, FC1, FC2, FC6, C3, CZ, and C4 represented the central lobe. The electrodes Cp1, CP2, P3, Pz, and P4 represented the parietal lobe. The electrodes T7, CP5, P7, M1, T8, CP6, P8, and M2 represented the right and left temporal lobes. The electrodes O1, Oz, O2, and POz are used to represent the occipital lobe.

the frontal lobe is associated with the acquisition of complex cognitive functions and behaviors. It has connections to communicate with other brain lobes [11]. The parietal lobe is related to spatial memory, the temporal lobe is associated with hearing senses, the central lobe processes visual elements, and the occipital lobe processes visual memory. Teplan [57] reported that F7 is located near regions for rational activities, Fz is located near intentional and motivational regions, F8 is close to sources of emotional impulses. The electrodes, F7, Fz, and F8, represent the frontal lobe. In the central brain lobe, the electrodes around C3, Cz, and C4 are related to sensory and motor functions. While the electrodes near to T7 and T8 are associated with emotional processors, the electrodes near to P7 and P8 in the same brain region are linked to certain memory functions. The electrodes O1 and O2 in the occipital lobe processes visual information.

2.7. Feature extraction and analysis

We analyzed statistical and spectral features of EEG signals. Feature sets were extracted after averaging EEG measurements of 32 channels. Similar to evaluating the entire task period as a block of epoch, multiplication of EEG samples by segmentation, replication, biasing, and overlapping is a common practice in literature. Atyabi and collaborators Atyabi and Powers [4], Atyabi et al. [5] studied the impacts of overlapping and non-overlapping sub-windows of EEG signal processing. Segmentation and replication methods were applied to a two-class motor imagery dataset and they found that the middle and end segments of the task period represented higher concentration toward the performing task compared to the beginning segments. Atyabi et al. also investigated EEG processing with biased non-overlapping and non-biased overlapping approaches. In biasing, extra samples were generated by replicating the regions of interest for given replication factor. They reported that any improvement in overall classification performance was due to the increased number of training samples. Standard overlapping using overlapping factors (25%, 50%, 75%, 90%) were tested and was found to be superior in higher window sizes (0.6 s and 0.8 s). Atyabi et al. reported no significance difference between 25% triangular overlapping and up to 90% standard overlapping in high window sizes (0.8 s). In our calculations, we used 1.0 s window size and 90% standard overlapping factor.

2.8. Classification features

As a baseline study, a variety of feature extraction techniques were implemented and applied to the EEG signals to cover time-domain and frequency-domain analysis of the signals. These methods based on statistical values [47,45], power spectral density [12], and time-domain energy.

1) Statistical-based features

Statistical features were initially developed for physiology signals [47], later also used in emotion recognition from EEG signals by many studies [45,52,56,62,63]. The six statistical descriptors, the mean, standard deviation, mean of the absolute value of the first derivative of the signal, mean of the absolute value of the first derivative of the normalized signal, mean of the absolute value of the second derivative of the signal, and mean of the absolute value of the second derivative of the normalized signal, were calculated. Means and variances are commonly computed in statistical representations. The first derivate approximates a gradient [47]. The means of the absolute values of the first derivative and the second derivative of the normalized signal are nonlinear combinations of other features. Since these features are calculated easily, they have an advantage in real-time applications. The disadvantage of statistical features lie in normalization for day to day variations. Many factors such as electrodes placement on different sessions or participant's daily mood may affect the statistics. To avoid day-to-day variations and their effects on statistics, we recorded the EEG signals in one session.

Given in equations 1–6, respectively. x(n) represents the EEG signal in time domain and N is the frame size.

$$\mu_x = \frac{1}{N}\sum_{n=1}^{N} x(n) \tag{1}$$

$$\sigma_x = \sqrt{\frac{1}{N}\sum_{n=1}^{N} (x(n) - \mu_x)^2} \tag{2}$$

$$\delta_x = \frac{1}{N-1}\sum_{n=1}^{N-1} |x(n+1) - x(n)| \tag{3}$$

$$\overline{\delta}_x = \frac{1}{N-1}\sum_{n=1}^{N-1} |\overline{x}(n+1) - \overline{x}(n)| \tag{4}$$

$$\gamma_x = \frac{1}{N-2}\sum_{n=1}^{N-2} |x(n+2) - x(n)| \tag{5}$$

$$\overline{\gamma}_x = \frac{1}{N-2}\sum_{n=1}^{N-2} |\overline{x}(n+2) - \overline{x}(n)| \tag{6}$$

The mean of the absolute value of the first derivative of the normalized signal $(\overline{\delta}_x)$ versus the mean of the absolute value of the second derivative of the signal(γ_x) for three emotional states and recall events after these emotional states are depicted in Fig. 3. The features $\overline{\delta}_x$ and γ_x are able to separate the positive events from the neutral and negative events.

2) Power spectral density (PSD) features

Nine features were extracted from the power spectral density (PSD) estimation of the EEG signal. These are the first five frequency peaks in the power spectral density estimation, skewness and kurtosis, the mean, and standard deviation of the corresponding PSD. The PSD estimations obtained from averaging periodograms of three emotions and recall events after these emotions. The fifth frequency peak was illustrated in Fig. 4.

Three Hjorth descriptors were calculated from power density spectrum. Activity, mobility and complexity parameters were extracted as in [12]. These parameters are commonly used in EEG analysis in mental task classification, sleep staging, and seizure lateralization. The spectral moments of order zero, two, and four are given in equations (7–9).

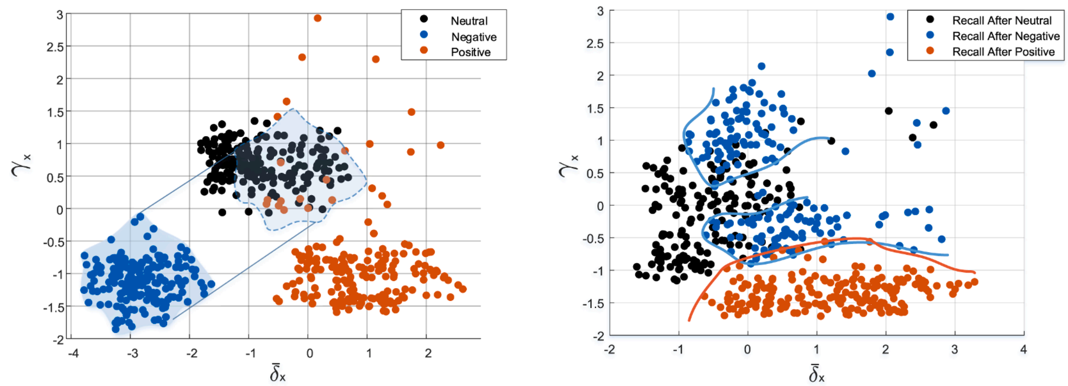

Fig. 3. Illustration of the mean of the absolute value of the first derivative of the normalized signal ($\bar{\delta}_x$) versus the mean of the absolute value of the second derivative of the signal(γ_x) for three emotional states and recall events after these emotional states. EEG data of participant #4 was used. Shaded regions bordered by a dotted line depict the original location of the cluster. The cluster is moved to the bottom left corner to illustrate the overlapping between clusters clearly.

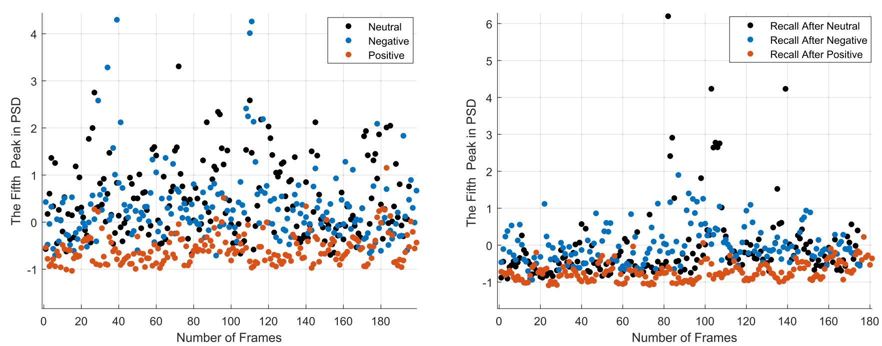

Fig. 4. The PSD estimation obtained from averaging periodograms of EEG signals of participant #4. a) Watching a set of emotion-annotated images as neutral, negative, and positive. b) Comparison of recall events after watching a set of emotion-annotated images.

$$m_0 = \int_{-\pi}^{\pi} S(\omega)d\omega = \frac{1}{T}\int_{t}^{t+T} f^2(t)dt \tag{7}$$

$$m_2 = \int_{-\pi}^{\pi} \omega^2 S(\omega)d\omega = \frac{1}{T}\int_{t}^{t+T} \left(\frac{df}{dt}\right)^2 dt \tag{8}$$

$$m_4 = \int_{-\pi}^{\pi} \omega^4 S(\omega)d\omega = \frac{1}{T}\int_{t}^{t+T} \left(\frac{df}{dt}\right)^4 dt \tag{9}$$

$$\text{Activity} : m_0 \tag{10}$$

$$\text{Mobility} : \sqrt{\frac{m_2}{m_0}} \tag{11}$$

$$\text{Complexity} : \sqrt{\frac{m_4}{m_2} - \frac{m_2}{m_0}} \tag{12}$$

$S(\omega)$ is the power density spectrum and $f(t)$ is the signal as a function of time. Activity, mobility, and complexity parameters are calculated as follows.

Activity and mobility define the square of the quadratic mean and

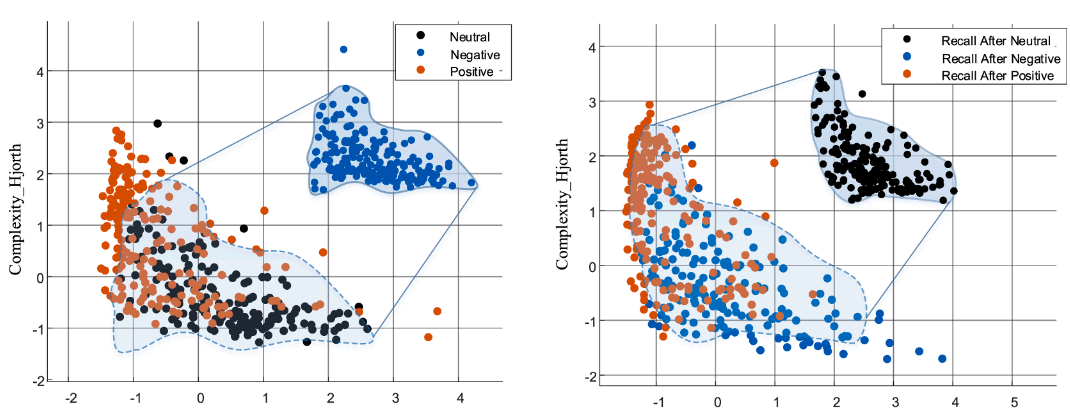

Fig. 5. The mobility and complexity parameters in separating emotional states and the recall events after those emotional states. EEG data of participant #4 was used. Shaded regions bordered by a dotted line depict the original location of the moved cluster. It has been moved to the upper right corner to illustrate the overlapping between clusters clearly.

the dominant frequency, respectively. Complexity represents the bandwidth of the signal. Fig. 5 represents the performance of the mobility and complexity parameters in separating emotional states and the recall events after those emotional states.

3) Energy feature

Teager energy operator (TEO) was extracted as another feature. It is defined in equation 13 and the normalized TEO of the selected events is represented in Fig. 6.

$$TEO = \frac{1}{N-1}\sum_{n=1}^{N-1} x(n)^2 - x(n-1)x(n+1) \tag{13}$$

Higuchi fractal dimension (HFD) algorithm has been employed to extract the HFD feature from the EEG data. To estimate the optimal Kmax parameter, which allows differentiating between three events as neutral, negative, and positive, we calculated the HFD feature for Kmax values, ranging between 2 and 312. Note that the frame size is 625 samples. The Kmax parameter cannot be higher than 312 since the maximum distance between compared samples is less than half of the frame size. We performed a one-way ANOVA to evaluate whether the HFD features of different Kmax parameters are statistically significant among events. None of the Kmax values was found statistically significant to differentiate between neutral and negative events. However, Kmax values between 2 and 5 produced statistically significant ($p < 0.001$) HFD features between negative-positive events and neutral-positive events. Accordingly, Kmax was chosen as 2 in our calculations. Fig. 7 shows the HFD feature for the events.

2.9. Feature selection

We employed a one-way ANOVA to assess the significance of each feature in the set. The mean of the power spectral density (PSD) estimation (p-value = 0.982), the mean of the signal (p-value = 0.9474), the mean of the absolute value of the first derivative of the signal (p-value = 0.0011), and the activity parameter of Hjorth descriptors (p-value = 0.982) were found to be not significant among neutral, negative and positive emotions. The same features and the standard deviation of the power spectral density (PSD) estimation (p-value = 0.104) were found to be not significant among three recall events corresponding to the three emotional stimuli. As a result, these five features were excluded from the feature set.

3. Experimental results

In this study, we measured the emotion and recall classification performances of combined EEG bands and brain lobes-based model (Table 1), brain lobes-based model (Table 2), EEG bands-based model (Table 3), and EEG bands and brain lobes-based model (Appendix A) by employing machine-learning methodologies. Table 1 summarizes the overall classification results per subject. Tables 2 and 3 present the averaged overall results. Results are expressed as a percentage of accurately classified samples per class type. The results were obtained using randomly selected 70–30% training-test data. Training and test sets are independent. The classification performance was measured ten times with different training and test sets. The results in the tables are the average values of the classification performances.

Support vector machines (SVMs) and K-Nearest Neighbors (KNNs) classifiers are designed as baseline classifier. In this study, we used open source machine learning library LibSVM [15] with RBF kernel, since it yielded higher accuracies in the cross-validation compared to other kernels. The parameters were optimized by using a 3-fold cross-validation over the training dataset. Other than the deep neural network classifiers, the SVMs, called maximum margin classifiers, are considered one of the best methods to deal with difficult classification problems in signal processing applications [7]. Maximizing the margin between two classes on the training data usually leads to a better classification performance on the test data, especially in high-dimensional spaces when using a limited number of samples [8].

The performance evaluation consists of accuracy, sensitivity, specificity, and F1-score, which were calculated by using the four outcomes from the classifiers. True positive (TP) refers to a case that a sample belongs to and the target event is correctly classified. False positive (FP), in which a sample belongs to another event is misclassified as the target event. True negative (TN) refers to a case where samples belong to another event classified correctly. False negative (FN), which refers to the case that a sample belongs to the target event, is incorrectly identified as another event. The percentage value for the accuracy, sensitivity, specificity, and F1-score can be calculated using equations (14), (15), (16), (17).

$$Acc = Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{14}$$

$$Se = Sensitivity = \frac{TP}{TP + FN} \times 100 \tag{15}$$

$$Sp = Specificity = \frac{TN}{TN + FP} \times 100 \tag{16}$$

$$F1\_s = F1_{score} = \frac{2TP}{2TP + FP + FN} \times 100 \tag{17}$$

The performance results of SVM and KNN classifiers during exposure to neutral, negative, and positive images and recall events after exposure to these three group of images are presented in Table 1, Table 2, and Table3.

As can be seen from Table 1, emotion classification associated with the exposure to neutral, negative, and positive images and recall event

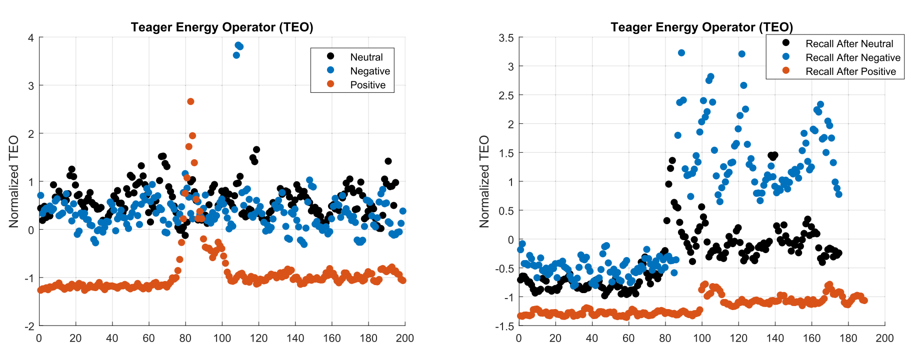

Fig. 6. Normalized TEO values of participant #4. a) Watching a set of emotion-annotated images as neutral, negative, and positive images. b) Comparison of recall events after watching a set of emotion-annotated images.

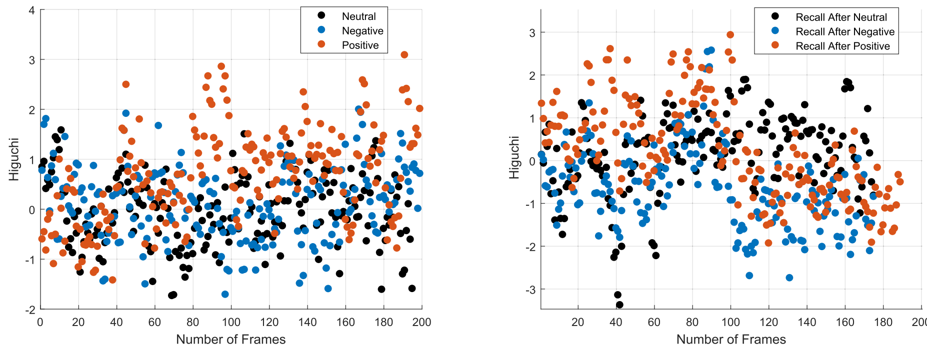

Fig. 7. HFD feature distribution in emotional states and recall events after the neutral, negative, and positive emotional states. EEG data of subject 4 (S-4) was used.

Table 1
The mean accuracy, sensitivity, specificity, and F1_score of classification results for SVM and KNN classifiers for each subject. All EEG bands and brain lobes were analyzed concomitantly. Bold letters indicate the averaged performance for all subjects.

Subject #	Overall performance during exposure to neutral, negative, and positive images						Overall performance of recall events after exposure to neutral, negative, and positive images					
	SVM			KNN			SVM			KNN		
	Acc	Se/Sp	F1_s	Acc	Se/Sp	F1_s	Acc	Se/Sp	F1_s	Acc	Se/Sp	F1_s
S-1	95.13	95.14/97.56	95.13	74.42	74.44/87.16	74.65	67.32	67.27/82.89	66.57	56.59	56.64/77.84	56.59
S-2	73.45	73.56/85.44	73.64	69.64	69.72/83.87	70.12	89.33	89.42/94.54	89.40	84.92	85.12/92.11	85.10
S-3	79.75	79.75/90.00	79.57	69.24	69.24/84.69	69.40	80.11	80.30/89.54	80.21	76.03	76.09/87.74	76.36
S-4	82.54	82.49/91.30	82.52	79.54	79.49/89.79	79.47	90.84	90.61/95.49	90.60	89.11	88.86/94.66	88.82
S-5	62.79	62.82/81.40	62.60	55.79	55.82/77.61	55.74	54.58	54.70/76.94	54.60	51.23	51.41/75.20	51.26
S-6	73.55	73.66/85.76	73.48	69.04	69.14/83.12	69.21	82.18	82.09/91.35	82.06	68.77	68.75/84.78	68.79
S-7	62.03	62.01/81.17	62.00	56.09	56.08/78.25	56.00	90.95	90.95/95.52	90.93	81.45	81.45/90.77	81.46
S-8	92.13	92.11/96.11	92.13	84.87	84.85/92.40	84.82	60.95	61.01/80.48	60.69	54.80	54.88/77.39	54.78
S-9	81.27	81.35/90.19	81.24	71.62	71.71/85.02	71.97	59.89	59.91/79.74	59.54	57.99	58.10/78.76	57.90
S-10	88.02	88/94.05	87.96	81.32	81.3/90.76	81.31	64.97	65.06/81.59	64.47	56.54	56.68/77.64	56.78
Average	**79.07**	**79.09/89.3**	**79.03**	**71.16**	**71.18/85.27**	**71.27**	**74.11**	**74.13/86.81**	**73.9**	**67.74**	**67.8/83.69**	**67.78**

Table 2
The overall mean accuracy, sensitivity, specificity, and F1_score of classification results for SVM and KNN classifiers. All EEG bands were analyzed concomitantly. Temporal, frontal, occipital, and parietal and central brain lobes combined (P + C) were investigated separately. Bold letters indicate the significant performances.

Overall performance during exposure to neutral, negative, and positive images									
Overall Performance (%)	*Brain lobe*	SVM				KNN			
		Acc	*Se*	*Sp*	*F1_s*	*Acc*	*Se*	*Sp*	*F1_s*
	Temporal	76.55	76.57	88.09	76.45	68.83	68.85	84.17	68.83
	Frontal	80.29	80.33	89.77	80.22	72.29	72.31	85.78	72.39
	Occipital	**82.51**	**82.53**	**90.94**	**82.48**	**75.92**	**75.95**	**87.51**	**76.03**
	Parietal +Central	79.99	80.04	89.52	80	70.79	70.83	84.83	70.89
Overall performance of recall events after exposure to neutral, negative, and positive images									
Overall Performance (%)	Brain lobe	SVM				KNN			
		Acc	Se	Sp	F1_s	Acc	Se	Sp	F1_s
	Temporal	71.46	71.42	85.7	71.17	65.67	65.63	82.8	65.6
	Frontal	71.22	71.26	85.49	71.18	63.95	64.03	81.79	64.03
	Occipital	**74.92**	**74.9**	**87.22**	**74.84**	**69.57**	**69.70**	**84.53**	**69.68**
	Parietal +Central	**74.88**	**74.9**	**87.33**	**74.71**	67.1	67.10	83.48	67.07

classification after exposure to these emotional states differ from subject to subject. This difference can be explained by the self-assessment analysis, which showed that neutral images did not elicit emotion while negative images induced strong negative emotions in participants. However, some of the participants indicated that positive images were not significantly associated with emotion. Therefore, only the neutral and negative set of images did elicit expected emotions. The emotion classification accuracies ranged from 62% to 95% by employing an SVM classifier. It ranged from 55% to 85% by the KNN classifier. Classification accuracies of the recall events under the influence of the set of neutral, negative, and positive images were calculated between 54% and 90% by the SVM classifier while it ranged between 51% and 89% by the KNN classifier.

Table 2 presents the accuracy, sensitivity, specificity, F1_score of classification results for temporal, frontal, occipital, and parietal and central brain lobes combined. The results from the ten participants were averaged in the table. All EEG bands were analyzed. The occipital brain region achieved the highest performance among the all brain lobes for emotion classification as 82.51% and 74.92% (by the SVM classifier) and 75.92% and 69.57% (by the KNN classifier). Comparable or better performance was achieved by analyzing each brain region than analyzing all brain regions in the classification of emotions and recall events under the influence the associated emotional states. The occipital lobe, represented by four electrodes O1, Oz, O2, POz and the combination of parietal and central brain lobes represented by the electrodes, FC5, FC1, FC2, FC6, C3, CZ, C4, Cp1, CP2, P3, Pz, and P4, achieved

Table 3
The overall mean accuracy, sensitivity, specificity, and F1_score of classification results for SVM and kNN classifiers. All brain lobes were analyzed concomitantly. Delta, theta, alpha, beta, and gamma EEG bands were investigated. Bold letters indicate the highest performance.

Overall performance during exposure to neutral, negative, and positive images									
		SVM				KNN			
	EEG band	Acc	Se	Sp	F1_s	Acc	Se	Sp	F1_s
Overall Performance (%)	Delta	55.19	55.24	77.08	54.91	47.28	47.30	73.31	47.27
	Theta	42.11	42.08	71.93	40.02	39.44	39.42	69.96	39.31
	Alpha	39.05	39.05	69.67	38.30	37.24	37.24	68.68	37.18
	Beta	41.19	41.18	70.91	40.33	38.62	38.61	69.45	38.52
	Gamma	**61.45**	**61.46**	**80.53**	**61.14**	**53.79**	**53.78**	**76.80**	**53.75**
Overall performance of recall events after exposure to neutral, negative, and positive images									
		SVM				KNN			
	EEG band	Acc	Se	Sp	F1_s	Acc	Se	Sp	F1_s
Overall Performance (%)	Delta	50.28	49.96	75.73	48.18	44.74	44.73	72.24	44.65
	Theta	41.06	40.48	72.86	37.69	39.20	39.15	69.89	39.05
	Alpha	40.56	40.17	71.82	38.10	39.04	39.04	69.63	38.92
	Beta	42.95	42.61	72.61	41.23	40.04	39.98	70.33	39.90
	Gamma	**56.99**	**56.98**	**78.80**	**56.63**	**51.02**	**51.05**	**75.67**	**50.92**

higher performance than the other brain regions. It is known that the occipital lobe is associated with processing of visual information. The frontal lobe achieved compatible performance with the occipital lobe in emotion recognition (80.29% by SVM and 72.29% by KNN). The electrode F8 in the frontal brain region is linked to emotions [57]. This may explain the high performance of the frontal brain region in emotion classification. The parietal and central brain lobes combined, performed similarly with the occipital lobe in the recall event classification under the influence of neutral, negative, and positive emotional states (74.88% by SVM and 69.57% by KNN). The recall events took place immediately after showing the three set of images expected to trigger neutral, positive and negative emotions in participants. Linked to processing of visual information, the occipital brain region might be still active during the subsequent recall events. Associated with the spatial memory and motor functions, central and parietal brain regions provided distinctive information in defining the three recall events.

Table 3 presents the performance results of the five EEG bands in classifying the three emotional states as neutral, negative, and positive, and in classifying the recall events under the influence of the three emotional states. The results from the ten participants were averaged in the table. The gamma band (31–100 Hz) achieved the highest performance among the five EEG bands. In emotion classification, it is 61.45% and 53.78% by the SVM and KNN, respectively. In recall classification, it is 56.99% and 51.02% by the SVM and KNN, respectively. However, the gamma band's performance was not compatible with the analysis of the EEG data from 0 to100Hz. Table 1 and Table 2 analyzed the EEG data from 0 to 100 Hz. Each EEG band is associated with specific type of mental activity. The beta band is associated with mental task processing; the theta band is associated with mind wandering; the alpha band is associated with memory performance; the beta band is associated with focus and thinking; the gamma band is associated with perception and cognition [23,10,28,33]. Our experimental results suggest that emotion and recall classification tasks should use the entire frequency range from 0 to 100 Hz.

A detailed investigation of the importance of each EEG band and brain region used to classify emotional states and the associated recall events is presented in Appendix A. The presented performances in Appendix A are in line with information presented in Table 2, where EEG bands were analyzed separately for the same tasks. Gamma band achieved the highest classification accuracies between 59.61 and 62.63% by SVM and between 52.51 and 54.01% by KNN in emotion classification. The performance was between 54.70 and 55.94% by SVM and 49.84–51.80% by KNN in recall event classification. The brain regions performed relatively comparable with each other, which is supporting the inferences from Table 2.

4. Discussions, reflections, and future works

This work focused on finding the effects of different emotional states on working memory. We designed our EEG data acquisition in three sessions. Each session started with a relaxation period. Next, a list of words and numbers was presented to participants to memorize. After memorization, the participants were shown a set of images from the IAPS database in order to arouse the intended emotion. Each session focused on stimulating one emotional state, such as neutral, negative, or positive. At the last step of each session, participants recalled the previously memorized information (words and numbers).

The EEG data were analyzed by using combined and separate EEG bands and brain regions. Our results showed that all EEG bands were important in emotion and working memory classification. Individual EEG bands did not provide satisfactory distinction between three emotional states and recall events (Table 3 and Appendix A), although the emotion classification performance was higher than the recall event classification. We can explain this by mentioning that all EEG bands are related to some associated memory functions and each EEG band carries unique information about memory-related activities. Hence, it is essential to process the full EEG signal frequency range while studying mental tasks and working memory.

Although brain regions are connected and have deep and complex interactions with each other, each brain region is linked to distinct functions. In our work, we grouped 32 EEG electrodes into five brain regions as frontal, temporal, occipital, central, and parietal. The details of the grouping can be found in the pre-processing section in this paper. We analyzed the central and parietal regions together. Each brain region is involved in memory-associated processes. Accuracy results of each brain region were found to be very similar in emotion and recall event classifications. The results suggest that the brain regions carry similar information regarding the mentioned tasks in this paper. In system designs, we may not need to analyze the EEG data from all brain regions. Instead, only one brain region can be analyzed to avoid complexity and to reduce computation time. Frontal, occipital, and parietal and central brain lobes performed compatible in emotion classification. Occipital, and parietal and central brain lobes performed compatible in working memory classification.

Signals associated with perception, cognition and emotion have been shown to be combined in complex ways. A recent study [44] reviewed the evidence that points to the existence of several connected systems within the central nervous system, with a high degree of association and interaction among them. This evidence has major implications for understanding how information flows in the brain and reveals a strong interaction of emotion with cognition, perception and action. For instance, it has been long known that the amygdala, also known as the center of emotion, has substantial bi-directional connections with the frontal, parietal and temporal lobes [2], but also with other deep brain sectors, such as the hippocampus [48]. In turn, these circuits enable upper brain lobes to be sensitive to a broad spectrum of sensory, motor and affective signals. This architecture allows for extensive communication and integration of emotional signals, so they can influence and be influenced by a large variety of signals. All in all, the alleged segregation of emotion and cognition emphasized in the literature is not supported by neuroanatomy [44]. This leads us into concluding that emotion interferes with all cognitive processes that primarily take place in the upper brain lobes, such as learning.

Analysis of different types of emotions and their influence on short-term, working memory may help us design better human–computer interfaces (HCI) and human–human interfaces (HHI). Such studies have an impact on many fields at many levels. Education is one of these fields. Students and teachers experience different types of emotions in academic settings. These emotions might be aroused prior or during their studies. Pekrun (2014) stated that "… *All these emotions can have important effects on students' learning and achievements. Emotions control the students' attention, influence their motivation to learn, modify the choice of learning strategies, and affect their self-regulation of learning…*" Pekrun and collaborators (2010) reported findings from a study on the role of emotions on students' self-regulated learning and academic achievement. Authors developed an academic emotions questionnaire (AEQ) and tested a cognitive-motivational model comprising the effect of emotion on academic achievement in 7 cross-sectional, 3 longitudinal, and 1 diary study among university and school students. Their study revealed a significant correlation between emotions and students' motivation and academic achievement, learning strategies, self-regulation, and cognitive resources. The study concluded that educational settings should acknowledge students' emotional states in order to improve the learning environment by addressing and adjusting the teaching material and approaches.

5. Reflections and future work:

In our current EEG data acquisition procedure, we introduced the focused information before showing the three set of IAPS images. The participants processed the information (numbers and words) before being exposed to emotional stimuli as a result of watching IAPS images. We may have had different experimental results if the participants processed the information (numbers and words) after exposure to the emotional stimuli. In our EEG data acquisition procedure, we asked participants to recall the previously presented information immediately after exposing them to the set of neutral, negative, and positive images. The participants could be asked to recall the previously presented information 5–10 min after showing the images. We obtained the EEG data from three sessions on the same day. We had only one trial per subject. Another experiment procedure can be set up by acquiring the EEG data of each session on different days or having several trials for the participant.

The electrode and brain region selection can also be done differently. For example, we could analyze the electrodes P7 and P8 in the parietal brain lobe, instead of the temporal lobe. In addition, we could analyze the central brain lobe by using the electrodes C3, Cz, and C4 only. The electrodes near these three electrodes could be analyzed with the neighboring brain regions or separately. We also designed two baseline classifiers, SVMs and KNN in this study. Since the focus of the paper was to verify the effects of emotions on working memory, we did not see a need to design a classifier system in deep neural networks (DNNs) or convolutional neural networks (CNNs), which have a complex architecture and high computation time. Nevertheless, one may want to design more advanced classifiers in order to evaluate similar scenarios.

6. Conclusion

In this study, the influence of neutral, negative, and positive emotions on the working memory has been investigated. By designing two baseline machine-learning models, support vector machines (SVMs) and K- nearest neighbor (KNN), the statistical significance of the EEG bands and the brain lobes were studied (at alpha level 0.001). Experimental results suggest that the memory recalls after exposure to neutral, negative, and positive images (to arouse neutral, negative, and positive emotions) differ from each other significantly. Each EEG band carries unique information in both emotion and memory recall classification tasks, so that entire EEG signal frequency range must be analyzed in similar studies. On the other hand, each brain region carries similar information regarding the classification tasks, thus only one of the brain regions can be analyzed to avoid complexity and high computation time. Our results show the possibility of designing an adaptive smart classroom (ASC) that will modify the teaching approaches based on students' emotional states. This study suggests that when evaluating working memory under various types of emotions, it is important to analyze all EEG bands concomitantly due to their statistical significant differences. On the other hand, our experimental results showed that the central, parietal, and occipital brain lobes carried more distinct EEG features that can be used to distinguish recall events after exposure to different emotional states.

CRediT authorship contribution statement

Buket D. Barkana: Conceptualization, Methodology, Software, Writing – original draft, Visualization, Data curation, Supervision, Investigation. **Yusuf Ozkan:** Software, Visualization, Investigation. **Joanna A. Badara:** Writing – review & editing, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. . The overall mean accuracy, sensitivity, specificity, and F1_score of classification results for SVM and KNN classifiers. Delta, theta, alpha, beta, and gamma EEG bands and temporal, frontal, occipital, and parietal brain lobes were analyzed disjointedly.

Overall performance during exposure to neutral, negative, and positive images										
	EEG band	Brain lobe	SVM				KNN			
			Acc	Se	Sp	F1_s	Acc	Se	Sp	F1_s
Overall Performance (%)	Delta	Temporal	54.14	54.17	76.62	53.43	47.99	48.01	73.75	47.87
		Frontal	54.18	54.22	76.52	53.56	47.46	47.48	73.33	47.45
		Occipital	57.01	57.05	77.83	56.57	50.24	50.27	74.60	50.18
		Parietal + Central	52.33	52.36	75.89	51.64	46.38	46.40	72.87	46.36
	Theta	Temporal	41.25	41.22	71.46	40.20	37.55	37.55	68.88	37.44

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Overall performance during exposure to neutral, negative, and positive images										
	EEG band	Brain lobe	SVM				KNN			
			Acc	Se	Sp	F1_s	Acc	Se	Sp	F1_s
		Frontal	41.79	41.75	71.84	40.25	38.83	38.83	69.57	38.75
		Occipital	39.80	39.78	70.62	38.20	37.04	37.04	68.65	36.94
		Parietal + Central	39.73	39.70	70.57	37.97	37.31	37.31	68.91	37.22
	Alpha	Temporal	41.25	41.22	71.46	40.20	37.55	37.55	68.88	37.44
		Frontal	40.57	40.57	70.67	39.73	39.02	39.02	69.64	38.90
		Occipital	39.25	39.26	69.87	37.42	37.02	37.02	68.54	36.87
		Parietal + Central	38.18	38.18	69.49	37.08	36.87	36.87	68.52	36.77
	Beta	Temporal	41.99	41.98	71.28	41.15	38.77	38.76	69.39	38.66
		Frontal	42.53	42.53	71.45	41.91	38.66	38.66	69.44	38.59
		Occipital	43.82	43.81	72.16	43.00	39.47	39.46	69.83	39.39
		Parietal + Central	40.58	40.57	70.64	39.83	38.80	38.80	69.54	38.67
	Gamma	Temporal	62.63	62.63	81.15	62.40	54.02	54.01	76.97	53.88
		Frontal	60.82	60.85	79.93	60.42	53.01	53.02	76.20	52.95
		Occipital	59.61	59.62	79.64	59.32	52.51	52.51	76.26	52.43
		Parietal + Central	60.19	60.21	79.75	59.81	53.82	53.82	76.81	53.76
Overall performance of recall events after exposure to neutral, negative, and positive images										
	EEG band	Brain lobe	SVM				KNN			
			Acc	Se	Sp	F1_s	Acc	Se	Sp	F1_s
Overall Performance (%)	Delta	Temporal	48.27	47.99	74.94	46.16	44.75	44.76	72.38	44.60
		Frontal	47.97	47.66	74.88	46.03	42.69	42.71	71.35	42.60
		Occipital	49.95	49.70	75.61	48.43	44.57	44.57	72.25	44.52
		Parietal + Central	48.33	47.89	75.27	45.19	43.66	43.62	71.86	43.56
	Theta	Temporal	40.55	39.95	72.65	37.34	38.26	38.19	69.49	38.12
		Frontal	41.00	40.41	72.89	37.67	37.88	37.87	69.17	37.73
		Occipital	38.73	38.03	72.53	34.49	37.12	37.06	68.88	36.96
		Parietal + Central	39.41	38.80	72.19	35.98	37.82	37.77	69.21	37.67
	Alpha	Temporal	40.55	39.95	72.65	37.34	38.26	38.19	69.49	38.12
		Frontal	41.52	41.01	72.92	38.68	39.13	39.10	69.83	39.01
		Occipital	41.29	40.84	72.23	38.74	37.78	37.77	68.98	37.67
		Parietal + Central	39.56	38.99	72.34	35.84	37.80	37.78	69.05	37.65
	Beta	Temporal	43.51	43.23	72.78	42.26	41.60	41.57	71.08	41.47
		Frontal	42.25	41.88	72.67	40.35	40.15	40.10	70.48	39.98
		Occipital	43.82	43.53	72.90	42.36	40.66	40.65	70.45	40.54
		Parietal + Central	41.52	41.12	72.30	39.64	41.12	41.10	70.81	41.00
	Gamma	Temporal	55.94	55.79	78.69	55.35	51.38	51.36	75.92	51.30
		Frontal	54.70	54.60	77.94	54.10	49.88	49.84	75.30	49.76
		Occipital	55.88	55.83	78.23	55.63	51.82	51.80	76.12	51.75
		Parietal + Central	54.81	54.86	77.49	54.56	51.00	51.06	75.58	50.97

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