



# Detection of multitask mental workload using gamma band power features

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Received: 8 February 2023 / Accepted: 21 February 2024  
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## Abstract

Cognitive fatigue occurs in various situations and is an essential condition to detect. In this study, how single and multi-tasking tests affect cognitive workload was examined, and multi-tasking was detected using electroencephalography (EEG) signals. In the cognitive workload paradigm, single-task tests with blocks 1 and 2 and multi-tasking tests with block 3 were created. EEG signals obtained from these blocks were treated as different frequency bands and lengths, and binary classification was performed. Two binary classifications were made: block 1–block 3 and block 2–block 3. According to the results, the highest classification accuracy for block 1–block 3 was obtained as 97.11% using the gamma frequency band and 5-s EEG length. For block 2–block 3, the highest classification accuracy was obtained as 90.88% using the gamma frequency band and 5-s EEG length. As a result, this study distinguished multi-tasking and single task with high classification accuracy. The developed model can be used to detect attention deficit and inability to focus. In addressing the prevalent challenges of distinguishing cognitive fatigue in single—task versus multitasking scenarios, our study offers a new method, which achieve a remarkable accuracy rate, thereby illuminating a new path in the research of cognitive fatigue.

**Keywords** Multitask · Mental fatigue · EEG · Classification

## 1 Introduction

The brain is a complex organ that controls thought, memory, emotion, touch, motor skills, vision, breathing, temperature, hunger, and every process that regulates our body. Together with the spinal cord, it forms the central nervous system [1]. Physiologically, the brain acts as central control over the body's other organs. It treats as a control mechanism over the rest of the body by making muscle activity patterns and releasing chemicals called hormones. This central control enables rapid and coordinate responses to changes in the environment. How individual brain cells work is now well understood, but how millions of brain

cells cooperate as a group remains to be deciphered [2]. Recent models in modern neuroscience treat the brain as a biological computer. The mechanism is very different from an electronic computer but very similar to computers in that it receives and stores information from the surrounding world, performs many parallel operations simultaneously, and gets fatigue while doing these operations [3, 4].

Fatigue is a very diverse issue with human physiology, emotional, behavioral, and cognitive components. It is a concept that includes various definitions, and it is not always physiological fatigue originating from the muscular system. One of the types of fatigue that affects daily life performance is cognitive fatigue which is defined as a psycho-biological condition that occurs as a result of prolonged movements.

Cognitive fatigue shows its effects in many areas of daily life. When the literature is examined, it has been stated that cognitive fatigue increases the rate of making mistakes in any work situation. It is a symptom of neurological disorders frequently encountered in adults [5, 6]. In addition to these, cognitive fatigue has been accepted as an essential determinant of performance in the field of sports and

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exercise [7, 8]. Although techniques such as electrodermal activity, magnetoencephalography, electrocardiography, and functional magnetic resonance imaging are used in the literature to detect cognitive fatigue, EEG is preferred in terms of revealing the neural activity, which is considered the source point for the detection of cognitive fatigue.

In recent studies Dehais et al. [9] measured mental fatigue and the electrophysiological effects of mental overload using a 32-channel EEG system in one of the studies on the detection of cognitive fatigue. Two experiments were conducted with the simulator that simulates the actual flight situation, and they revealed that alpha, theta, and beta band powers affect the detection of cognitive fatigue. They could distinguish mental overload and mental fatigue with a classification accuracy (CA) of 89.1% [9]. In another study, Trejo et al. experimented with 16 people with EEG signals they received over 30 channels. A 3-state fatigue model was developed using the Bayesian classification algorithm with the obtained EEG signals [10]. In another study in the literature, Sun et al. performed a 20-min attention test on 26 people. With the algorithm used in this study, an CA of 81.5% was obtained in the classification of fatigue and rest through cross-validation [11]. In another study, Papakostas conducted a 76-session cognitive experiment with 19 male and female participants using the Wisconsin card sorting test and a different version of this test. Resting cognitive workload classification was performed using the support vector machine algorithm with the EEG signals recorded during the experiment, and an CA of 67% was obtained [12]. Similar to the studies provided above, the classification accuracies obtained in our study are presented in Table 2.

There are also studies investigating the effects of different tests on detecting cognitive fatigue. Chai et al. compared the performance of three different tests in detecting cognitive workload using EEG signals. For this purpose, the power spectral density, power spectral entropy, wavelet transform, autoregressive features, AX-continuous performance test, psychomotor alertness test, and Stroop Test were compared with the Bayesian classification algorithm. According to the autoregressive feature method results, the highest CA of 75.95% was obtained in the AX-continuous performance test, 75.23% in the psychomotor alertness test, and 76.02% in the Stroop Test [13]. In their study, Peng et al. investigated the effect of mental fatigue caused by different tasks using functional near-infrared spectroscopy. In addition to distinguishing fatigue from non-fatigue, early signs of fatigue have also been studied to provide an early warning of fatigue. For this purpose, 36 participants were randomly divided into three groups, and one of the psychomotor alertness tests, cognitive study, or simulated driving test was performed with each group. The tests were carried out at three different times of the day,

morning, noon, and evening. Before cognitive tests (psychomotor alertness test, cognitive study, or simulated driving test), n-back ( $n=1$ ) and multidimensional fatigue inventory (Multidimensional Fatigue Inventory, MFI-20) tests were performed. As a result of these tests, those with an MFI-20 score less than 2.57 were not identified as cognitively tired, while those with an MFI-20 score above 2.57 were determined as cognitively tired. In addition, according to MFI-20 and n-back dual evaluation, those with a score greater than 3 were determined as severe fatigue, and those with a dual evaluation score of less than 3 were determined as moderate fatigue. The results both showed the functional connection between brain regions during cognitive fatigue and were discussed in classification accuracy. Accordingly, 85.4% CA was obtained in the binary classification in which fatigue and fatigue were compared, and five-fold cross-validation was performed. In the classification process where mild and severe fatigue were compared, an CA of 82.8% was obtained [14]. In another study in the literature [15], Lim et al. used an open-access EEG dataset for multitasking mental workload activity caused by a single-session simultaneous capacity experiment with 48 participants. In this study, which is closest in content to our study, the participants were asked to perform the Vienna test system's simultaneous capacity (SIMKAP) test module [16]. SIMKAP is a commercial psychological test created by Schuhfried GmbH to assess an individual's tolerance for multitasking and stress. While the test was designed as an assessment tool to screen personnel's multitasking abilities in multitasking-heavy occupations such as air traffic management, it has also been applied in various research scenarios involving multitasking [17–19]. The SIMKAP multitasking test is a test that requires participants to highlight the same items by comparing two separate panes while answering auditory questions, which can be arithmetic, comparison, or data searching. When the results were examined, low, moderate, and high fatigue levels were distinguished, with a mean CA of 69%. Studies have generally investigated the effect of different cognitive tests on creating workload. In the study of Lim et al., they classified the beginner, intermediate and advanced cognitive workload groups with the multitasking test they created. However, this study did not investigate how single and multitasking tests affect cognitive workload [15]. The study of Karim et al. delved into the intricate nature of cognitive fatigue (CF) and its ramifications on day-to-day performance. They highlighted that CF results in a decline in cognitive system performance, leading to exhaustion. For the purpose of their study, an experimental setup was established to artificially induce cognitive fatigue among subjects. During this process, EEG signals were meticulously collected from the participants. The primary objective of the study was to ascertain the presence or absence of

cognitive fatigue. Impressively, based on the EEG readings, the proposed method managed to detect cognitive fatigue in the subjects with a commendable accuracy of 88.17% [20]. In the study, Gao et al. underscore the utility of EEG signals as an effective method for fatigue detection. This approach intuitively captures the mental states of drivers. Existing studies, however, have yet to thoroughly explore multi-dimensional features of EEG signals, which presents challenges given their inherent instability and complexity. Additionally, a prevailing trend in the current literature is the treatment of deep learning models primarily as classifiers, often overlooking the distinctive features of various subjects captured by the model. To address these gaps, the authors introduced a novel multi-dimensional feature fusion network that integrates the Gaussian Time Domain Network and the Pure Convolutional Spatial Frequency Domain Network. The proposed methodology excelled in discerning between alert and fatigue states, demonstrating accuracy rates of 85.16% and 81.48% on custom-built and SEED-VIG datasets, respectively. This performance surpassed existing benchmarks. Moreover, the study delved into the significance of each brain region in fatigue detection using brain topology maps and examined the variations across different frequency bands for diverse subjects in both alert and fatigued states via heat maps. This comprehensive approach offers fresh perspectives in brain fatigue research and holds promise for further advancements in the domain [21].

In line with the previous studies above mentioned, in this study, we contribute to the literature by detection multitask cognitive workload with a novel pattern recognition strategy, which extracts meaningful features from the EEG signals using only 5-s EEG length of the gamma frequency band. In the cognitive workload determination task created for this purpose, the participants were first asked to answer the questions involving mathematical operations in the first block. Then the same experimental procedure was repeated with similar questions in the second block. In the third block, where both the mathematical operations and the news recording were played, the participants were asked to listen to the news recordings played in the background while answering the mathematical questions. At the end of the experiment, the participant was reminded that questions would be asked from the news recording, and they were asked to listen carefully to the news recording. Thus, the difference in cognitive workload between the blocks was classified by recording EEG data in the single task block 1 and block 2, where only mathematical operations were performed. Mathematical operations were performed in multitasking block 3, and the news recording was played. As a result, this study investigated the effect of single tasks and multitasking on cognitive workload. To the best of our knowledge, this study is the first attempt to compare single and multitask. Single and multi-tasking EEG signals were

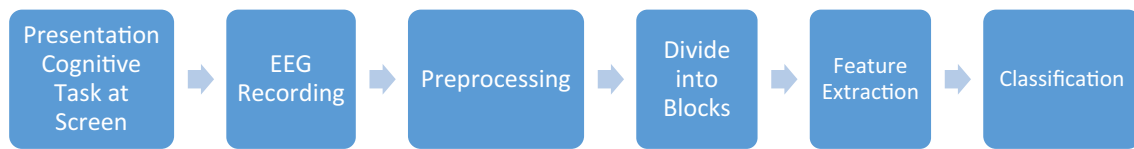
distinguished using the gamma frequency band and EEG length of 5 s, with the highest accuracy of 97.11%. In essence, our work pioneers a fresh perspective on understanding cognitive fatigue, bridging the gap between single-task and multitasking implications. By providing a robust methodological approach coupled with high accuracy, we believe to set a new benchmark in cognitive fatigue research. Moreover, the proposed method can be able to reveal the multitask cognitive fatigue-based reason of poor performance of EEG based applications, which required attention and focusing ability such as brain-computer interface, decision making and problem solving. From these perspectives, it is thought that the proposed method will make a significant contribution to the literature, as this issue has not been studied directly in the literature.

## 2 Materials and methods

The block diagram of the transactions carried out within the scope of this study is shown in Fig. 1. Firstly, the paradigm that enables the detection of cognitive workload was shown to the participant on the LED screen. The participant's brain's electrical response to stimuli throughout the experiment is recorded. In the preprocessing phase following the EEG recording, we meticulously filter out high-frequency components that are extraneous to the inherent EEG signals, and rigorously eliminate any noise. This careful preprocessing not only refines the signal quality but also significantly enhances the success rate of subsequent classifications. EEG data are then divided into blocks with rest and cognitive workload. The resulting blocks are divided into sub-blocks of 1 s, 3 s, and 5 s. The classification process is performed by extracting the features from each sub-data block obtained.

### 2.1 Paradigm

The paradigm prepared to make a cognitive workload consists of 4 parts. First, the participant rested for 5 min by looking at the '+' symbol on the computer screen, which was named as block 0. Then, the cognitive workload blocks, in which the participant solves problems mentally were started. In the first of these blocks, the participant mentally solved the questions displayed on the computer screen for 5 min. Afterwards, a 1-min rest break was given. At the end of the rest, the second block was utilized. In the second block, the participant mentally solved the questions on the screen in front of him for 5 min, similar to block 1. After the second block, a 1-min rest break was given. Finally, in the third block, the participant simultaneously listened to the news recordings playing in the background while mentally solving the questions that appeared on the screen in front of



**Fig. 1** Flowchart of the proposed method

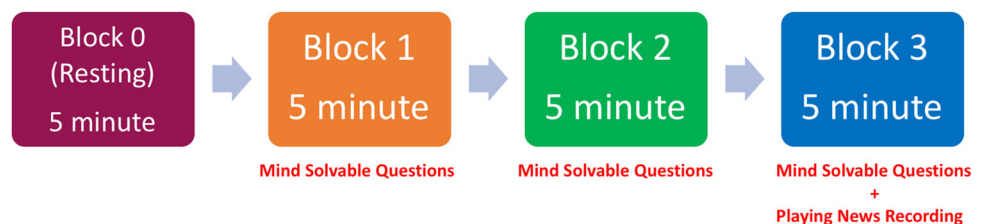
him for 5 min. Before the experiment started, the participant was reminded that while solving the questions in the last block, he had to listen to the news recording, and he was told that at the end of the experiment, questions about the news recordings would be asked. Thus, the participants simultaneously listened to the news recording while solving the questions in the third block. At the end of the experiment, questions about the news were asked, and the answers were noted. Experiment blocks and duration are shown in Fig. 2.

In block 1, block 2, and block 3, where the cognitive workload was made, multiple-choice and mentally solvable questions were asked. The difficulty levels of the questions are adjusted as equally as possible for block 1, block 2, and block 3. A–B–C–D options were selected, and labels were attached to the A–S–D–F keys on the keyboard, respectively, and these options were brought side by side to create fewer artifacts. The paradigm created within the scope of the study is shown in Fig. 3.

## 2.2 EEG recording

Experiments were conducted with a total of eight participants, five males (mean age  $30 \pm 6.05$ ) and three females (mean age  $30 \pm 5.29$  years). While the sample size of eight participants might limit broad generalizations, the depth of individual data provides a rich foundation for understanding the phenomena under investigation and sets a robust precedent for subsequent larger-scale studies. Participants do not have any visual or neurological disorders. In addition, all participants are right-handed. None of the participants had participated in a similar experiment before. Karadeniz Technical University Health Sciences Institute Ethics Committee approved data collection. All participants signed the consent form provided by the board before the experiment began.

**Fig. 2** Blocks in the experiment and their duration



EEG data were recorded using the actiCHamp (Brain Products GmbH, Gilching, Germany) device, using electrodes placed in 32 channels according to the international 10–20 standard. The sampling frequency was determined as 250 Hz, and the data were recorded using the 'Fz' reference electrode and the ground electrode in the forehead region. During the experiments, the conductivity-enhancing gel was used so that the impedances of all electrodes were below 5 k $\Omega$ . The electrode array used for data acquisition is shown in Fig. 4.

It is assumed that the participants did not use any neurological drugs based on their own statements, strictly followed the given task, focused on the subject, and adhered to the experimental rules.

## 2.3 Preprocessing

In the preprocessing stage, five different band-pass filters were applied to the EEG data obtained from the participants, namely 0.1–4 Hz delta (D), 4–8 Hz theta (T), 8–13 Hz alpha (A), 13–30 Hz beta (B), and 30–100 Hz gamma (G). This way, the effect of different band components on classification was investigated.

Within the scope of the study, a fourth-order Butterworth infinite impulse response (IIR) bandpass filter [22, 23] was used. The input and output signals to the filter are related to the convolution sum.

$$y(n) = \sum_{k=0}^{\infty} h(k)x(n-k) \quad (1)$$

In equation  $x(n)$ ,  $y(n)$  and  $h(n)$  represent the unit impulse response of the input, output, and filter, respectively, and  $N$  represents the degree of the filter.

In practice, it is impossible to calculate the IIR filter's output as in Eq. (1) because the length of the pulse response is very long (in theory, infinite). Instead, the IIR filtering equation is expressed recursively.

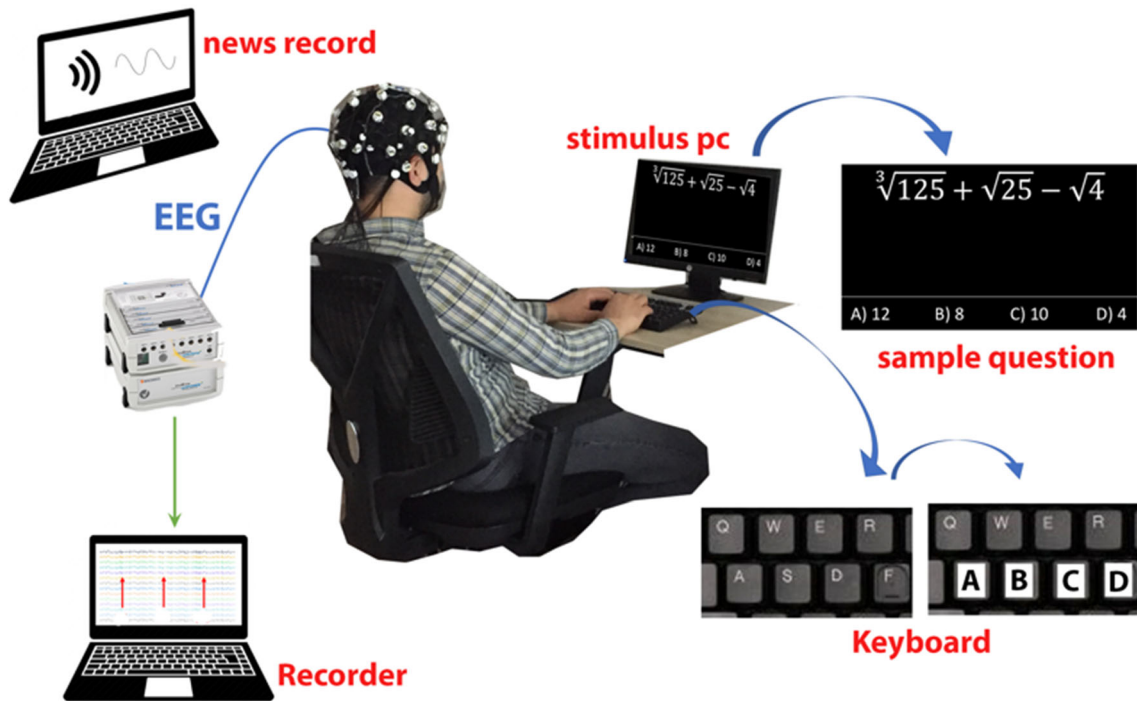


Fig. 3 The paradigm created for the detection of cognitive fatigue

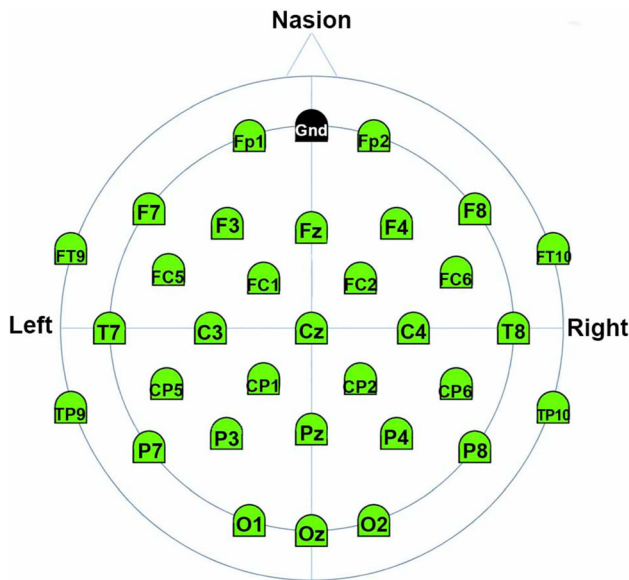


Fig. 4 Arrangement of the electrodes used in data acquisition

$$\begin{aligned}
 y(n) &= \sum_{k=0}^{\infty} h(k)x(n-k) \\
 &= \sum_{k=0}^N b(k)x(n-k) + \sum_{k=0}^M a(k)x(n-k)
 \end{aligned}
 \tag{2}$$

Here  $a_k$  and  $b_k$  show the filter coefficients.

Butterworth, one of the IIR filter types, was used in the band-pass filter design. The transfer function of the filter;

$$B(\omega) = \frac{1}{\left[1 + \left(\frac{\omega}{\omega_0}\right)^{2n}\right]^{1/2}}
 \tag{3}$$

Here  $n$  is the order of the filter, and  $\omega$  is the angular frequency.

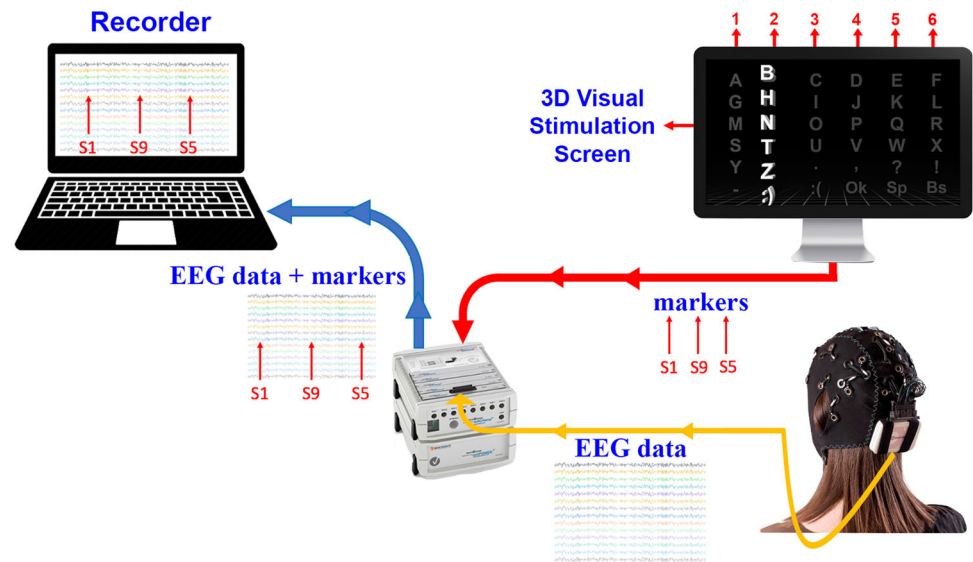
### 2.4 Splitting into blocks

In the blocking stage, each of the data that was separated into different frequency components in the preprocessing step was divided into block 1, block 2 and block 3 groups. (It is worthwhile mentioning that block 0 was not considered in the feature extraction and classification process.). The connections between the computer where the stimulus presentation is made, the computer where the data are recorded, and the EEG device are shown in Fig. 5. The trigger information (stimulus; S1, S2, S3, Etc.) about which block started on the computer where the stimulus presentation is made is sent to the EEG device with a delay of 1 ms via the parallel port. The brain's electrical activity comes from the electrodes, and this trigger information is combined in the EEG device and sent to the recording computer in a time-locked manner.

At the beginning of the rest block, the 'S1' trigger signal and the 'S2' trigger signal at the end are sent to the EEG device from the parallel port. Similarly, trigger marks 'S3' and 'S4' for the start and end of block 1, trigger marks 'S5'



Fig. 5 The experimental setup



and 'S6' for the start and end of block 2, and finally, 'S7' and 'S8' trigger signals are sent for the start and end of block 3, respectively.

## 2.5 Feature extraction

The spectrogram method was used to obtain time–frequency signal separation.

$$E_f = \sum_t |X(f, t)|^2 \quad (4)$$

Here,  $X(f, t)$  represents the time–frequency representation of the original  $x(t)$  signal and the energy margins in the  $E_f$  frequency domain. The band power is denoted by  $E_B$  and is obtained by summing the energy margins in the band and is calculated as shown in the equation below.

$$E_B = \sum_{f \in B} E_f \quad (5)$$

In the study, the blocks with the workload were compared. Accordingly, binary classification operations were carried out in block 1 and block 2, where single tasks were performed, and in block 3 where multitasking was performed. For example, the classification process was performed to compare block 1 and block 3 with the band power features extracted from the delta frequency band and the 0.25 s long EEG segments. For this purpose, the single task and multitasking block in the same length and frequency band were brought together to form the data set to be classified.

## 2.6 Classification

For classification purpose, a data matrix of size  $D \times 32$  and a label matrix of size  $D \times 1$  each are brought together. Here,  $D$

varies according to the length of the EEG piece used. For example, when EEG pieces of 1 s are used, 300 pieces of EEG are obtained because the blocks take 5 min, that is, 300 s. Since 300 samples come from single-task blocks (block 1 or block 2) and 300 samples come from multitasking blocks (block 3),  $D=600$  here. Similarly, when the EEG length is 3 and 5 s,  $D$  equals 200 and 120, respectively.

The classification was carried out with artificial neural networks (ANN) classification algorithm using the data set obtained depending on the EEG segment length and frequency component.  $N$  feature vectors were randomly divided into three parts, each time as 50% training, 25% validation, and 25% testing, and the classification process was repeated 50 times in total. The results section shows the average test accuracies obtained as a result of the classification process repeated 50 times.

A two-layer ANN model with one output neuron and one hidden layer was used in the classification step. The ANN model is shown below.

$$\hat{y} = \tilde{g} \left( \sum_{j=1}^M w_{1j}^{(2)} * g \left( \sum_{i=1}^d w_{ji}^{(1)} * x_i + w_{j0}^{(1)} \right) + w_{11}^{(2)} \right) \quad (6)$$

Here  $(x_i)$  is the  $i$ th input,  $(w_{ji}^{(k)})$  is the layer weight between the  $i$ th neuron and the  $j$ th neuron in the  $k$ th layer,  $(g)$  is the tangent sigmoid function, and  $(\tilde{g})$  is the linear function. Also,  $(d)$  represents the size of the input vector. Total error for the entire data set;

$$J(w) = -\frac{1}{N} \sum_{n=1}^N [y_n \log \hat{y}_n + (1 - y_n) \log (1 - \hat{y}_n)] \quad (7)$$

Here  $(N)$  represents the total number of samples in the signal,  $(\hat{y}_i)$  is the estimated value calculated by the neural

network model, and  $(y_i)$  is the actual label value of the sample. The created ANN model is shown in Fig. 6.

In the study, support vector machine (SVM) and linear discriminant analysis (LDA) were also used for comparison purposes. Since these methods are widely known and not in the proposed method, their detailed explanation is not given here.

**Artificial Neural Network (ANN):** After numerous configurations and preliminary tests, our optimal ANN model comprises a specific number of hidden layers, neurons in each layer, a learning rate of 0.01, a Rectified Linear Unit (ReLU) activation function, and a maximum of 50 epochs.

**Linear Discriminant Analysis (LDA):** Our selection of the 'Linear' discriminant type was grounded in its efficacy during our preliminary tests.

**Support Vector Machine (SVM):** The 'Linear' kernel was favored due to its robust performance for our dataset. Additionally, the box constraint was set at 1, and the kernel scale parameter was also determined to be 1 after comprehensive trials. Our aim in detailing these parameters is to ensure transparency in our methodologies and to highlight the thoroughness in our experimental design.

### 3 Results

Within the scope of the study, EEG data of block 1-block 2 with single task and block 3 with multitasking were classified using different frequency bands and EEG signals of different lengths. For this purpose, block 1-block 3 and block 2-block 3 EEG data for all individuals separately in delta (D), theta (T), alpha (A), beta (B), and gamma (G) frequency bands 1, 3, and CA was obtained using 5-s EEG segments and is shown in Figs. 7 and 8. As seen from the figures, the first column contains block 1-block 3, the

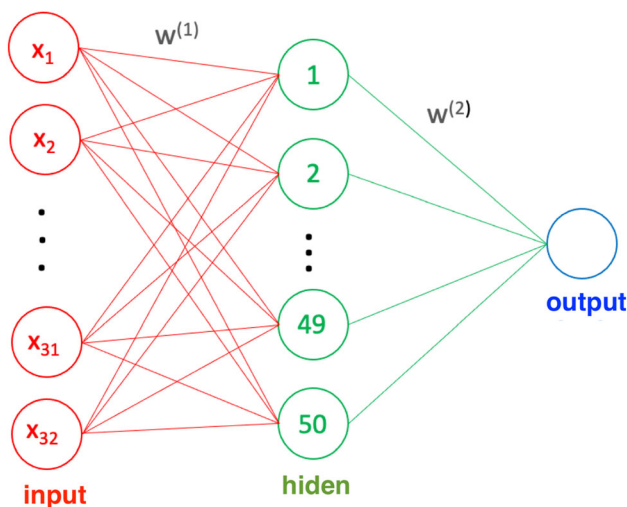


Fig. 6 Artificial neural network model

second column contains block 2-block 3, and the rows contain the CA results of the individuals.

CA results are given using radar charts. Radar charts are a type of chart used to show the effects of different frequency bands and EEG signals of different lengths on CA at the same time. The effects of D, T, A, B, and G frequency bands on the diagonals and the 1, 3, and 5-s (s) EEG signal lengths on the CA are seen on the inner lines of the radar charts. The CAs of 1-s EEG lengths are shown with green dots, and the CAs of 3 and 5-s EEG lengths are shown with blue dashed and solid red lines, respectively. In radar charts, the CA level starts from 50%, increases 10 by 10, and reaches 100%.

Figures 7 and 8 show that the gamma band is the most effective frequency band in both block 1-block 3 classifications and block 2-block 3 classifications. This situation is compatible with the literature. Studies have shown that as the cognitive workload increases, there is an increase in activation in EEG oscillations, especially in the gamma band [24, 25]. After the gamma band, the highest CA is obtained by using the beta band. The lowest CA is obtained by using the delta frequency band. According to the results obtained, it is seen that the use of 5-s EEG segments increases the classification performance.

Average classification accuracies and standard deviation values for all subjects shown in Table 1 were obtained by averaging the CAs in Figs. 7 and 8. When the mean values are examined, a more general interpretation can be made. In this context, it is seen that the gamma frequency band is the most effective frequency range in both block 1-block 3 and block 2-block 3 CAs. The worst CA was obtained with 59.84% accuracy using the delta frequency band and 1s EEG segment. Considering EEG lengths, the highest CA is obtained with 91.88% accuracy using 5-s EEG segments and the gamma frequency band. The most valuable information obtained from the mean values shown in Table 1 is that block 1-block 3 CAs are higher than block 2-block 3 CAs. Accordingly, since the person was less tired at the beginning of block 1, higher CA was obtained compared to block 3. As the process progressed, cognitive fatigue increased, so the CA obtained from the comparison of block 2 and block 3 was lower than the CA obtained from the comparison of block 1 and block 3. The participant count was determined based on the literature, and the consistency of the results was proved by the standard deviation values for classification accuracies, as displayed in Table 1. The table indicates that the standard deviation values are satisfactorily low.

The classification was done with different features and algorithms using 5-s EEG segments and gamma frequency bands. For this purpose, classification results were obtained by ANN, SVM, and LDA algorithms using skewness,

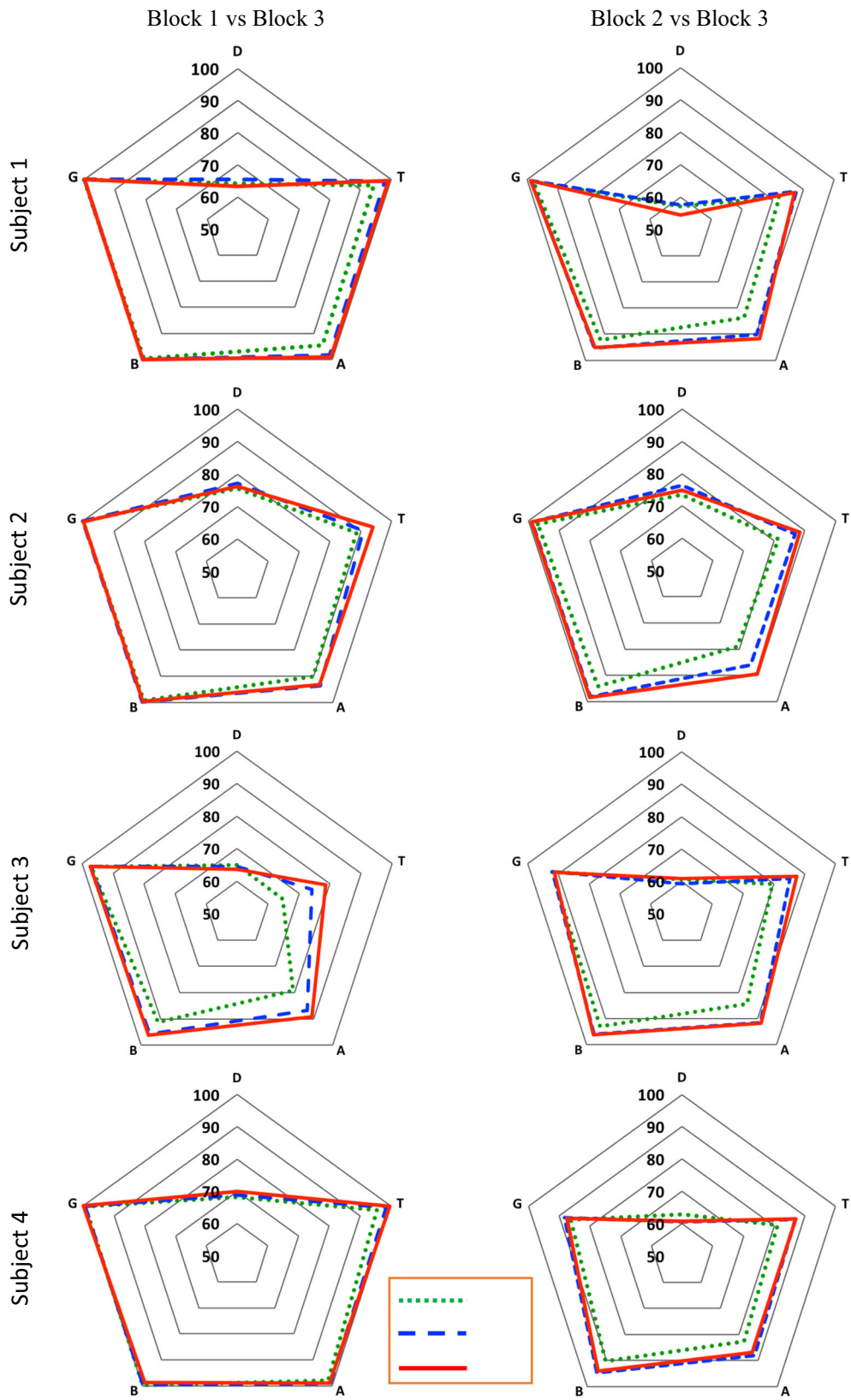


Fig. 7 Classification accuracies for subject 1, 2, 3 and 4



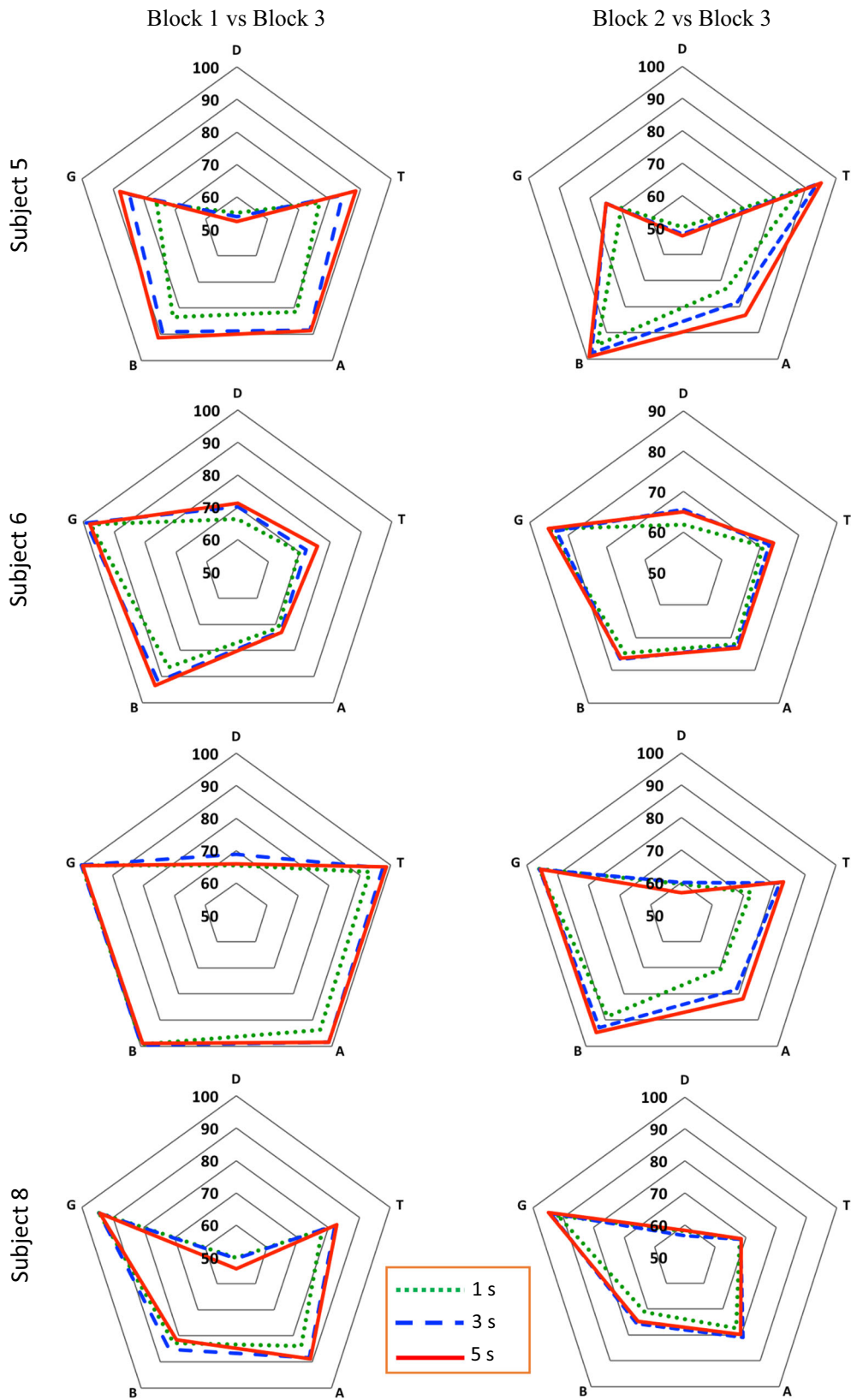


Fig. 8 Classification accuracies for subject 5, 6, 7 and 8

**Table 1** Average CAs obtained for all persons

	Block 1 vs Block 3			Block 2 vs Block 3		
	1 s	3 s	5 s	1 s	3 s	5 s
D	63.7 ± 44.28	64.81 ± 6.83	63.64 ± 8.71	60.47 ± 4.36	60.53 ± 7.03	59.84 ± 9.28
T	82.65 ± 3.25	87.20 ± 4.18	89.64 ± 4.47	77.94 ± 3.63	82.82 ± 4.92	83.69 ± 6.42
A	86.53 ± 2.61	90.72 ± 3.43	91.13 ± 4.44	77.85 ± 3.45	83.32 ± 4.46	84.78 ± 6.29
B	92.70 ± 2.09	95.09 ± 2.72	94.93 ± 3.34	87.35 ± 2.65	90.91 ± 3.47	91.10 ± 4.34
G	95.56 ± 1.13	96.84 ± 1.61	<b>97.11 ± 2.11</b>	89.38 ± 2.38	90.71 ± 3.90	<b>91.88 ± 4.29</b>

kurtosis, root mean square statistical features, band power, and higher-order spectral features and are shown in Table 2.

## 4 Conclusion and discussion

The most EEG-based cognitive fatigue detection studies either looked at the effect of different test types on creating cognitive workload or looked at the workload level of multitasking. There are some EEG based approaches which required attention and focusing ability such as brain-computer interface, decision making and problem solving. While one of the important reasons of poor performance of such studies is attention and focusing, it could not be easily detected since it highly depends on mental workload of the user. Considering that the issue of multitasking cognitive fatigue has not been directly studied in the literature, it can be said that the main novelty of our work has great potential to reveal multitasking cognitive fatigue using only a 5-s EEG length of gamma frequency. In other words, in this study, unlike the literature, how single and multitasking tests affect cognitive workload was investigated and classified. In this context, single-task and multitask tests were made, and the classification process was carried out. Classification processes are discussed in terms of both different frequency bands and different EEG lengths. According to the results obtained, single-task and multitask EEG signals were separated from each other with the highest classification accuracy using the gamma frequency band. The most effective EEG length was determined as 5 s. The classification accuracy obtained in the first single task (block 1) and multitasking (block 3) comparison is higher than in the second single task (block 2) and multitasking comparison.

**Table 2** Accuracies of different features and classifiers

	Statistical features	Band power	Higher-order spectral
ANN	85.30	<b>91.88</b>	88.47
LDA	81.11	86.34	87.29
SVM	86.12	90.12	89.91

This is because the person gets more and more tired as time progresses. Using the proposed method, the highest CA in block 1–block 3 comparisons were obtained in the gamma frequency band using a 5-s EEG segment with an accuracy of 97.11%. Again, in the comparison of block 2–block 3, the highest CA was obtained in the gamma frequency band with an accuracy of 90.88% using a 5-s EEG segment. Within the scope of the study, single-task and multitasking were considered as binary classification problems and were distinguished by their high classification accuracy. This will be useful to determine whether the person is focusing on a single task or multi-tasking. In such detection, it can be used in systems such as the brain-computer interface, where the person is asked to focus on a single target to determine whether the person is focused or not. It can also be used to determine whether people have an attention deficit.

The most EEG-based cognitive fatigue detection studies primarily focus on the effect of different test types on creating cognitive workload or examine the workload level of multitasking. Our work fills a gap in the literature by exploring the impact of both single and multitasking tests on cognitive workload. Specifically, we examined and classified the differences between these two types of tasks. Unique to our study, we analyzed single-task and multitask tests, undertaking classification processes across varied frequency bands and EEG lengths.

According to our findings, single-task and multitask EEG signals were most distinctly differentiated using the gamma frequency band. Notably, the optimal EEG segment length was 5 s. A possible explanation for higher classification accuracy in the first single task (block 1) compared to the second single task (block 2) is the progressive cognitive fatigue experienced by the subject over time. Using our method, we achieved an impressive classification accuracy of 97.11% in Block 1—block 3 comparisons, while the comparison of block 2—block 3 yielded an accuracy of 90.88%, both utilizing the gamma frequency band over a 5-s EEG segment.

These results not only provide insights into the distinct neural patterns underlying single-tasking versus multitasking but also hold potential practical implications. Our findings underscore the importance of considering task type and progression when assessing cognitive fatigue and

workload using EEG. The high classification accuracy supports the potential application of our method in real-world scenarios, such as brain-computer interfaces where task focus is critical. Furthermore, these results can be instrumental in designing interventions for individuals with attention deficits or for settings where rapid task-switching is required. Future research could delve deeper into understanding the neural mechanisms driving these differences and explore the scalability of our method across diverse populations and tasks.

As future work, we intend to improve CA performance in two ways. One of them is applying different kinds of pre-processing techniques, including normalization and principal component analysis methods. Secondly, we aim to improve the proposed method to find subject-dependent filter frequencies, which will provide specific filter for each participant. Moreover, we want to test the proposed method with other kinds of EEG equipment including wireless EEG sensors and different machine learning algorithms including  $k$ -nearest neighbor and decision tree. In addition to CA metric, we will apply polygon area metric (PAM) [26], which is a new, simple and effective promising technique for the evaluation of the performance of classifiers in machine learning applications.

**Acknowledgements** The data used in this study were recorded at Atatürk University Sports Sciences Application and Research Center. This study was supported by the Inter Computer Electronics Ltd. and Brain Products GmbH.

**Funding** Open access funding provided by the Scientific and Technological Research Council of Türkiye (TÜBİTAK).

**Data availability** The dataset supporting the conclusions of this article is available in the Kaggle public repository <https://www.kaggle.com/datasets/onurerdemkorkmaz/multi-task-mental-workload-eeeg-dataset>

## Declarations

**Conflict of interest** The authors declare no conflicts of interest.

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