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RESEARCH ARTICLE

Monitoring nap deprivation-induced fatigue using fNIRS and deep learning

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Abstract

Fatigue-induced incidents in transportation, aerospace, military, and other areas have been on the rise, posing a threat to human life and safety. The determination of fatigue states holds significant importance, especially through reliable and conveniently available physiological indicators. Here, a portable custom-built fNIRS system was used to monitor the fatigue state caused by nap deprivation. fNIRS signals in ten channels at the prefrontal cortex were collected, changes in blood oxygen concentration were analyzed, followed by a deep learning model to classify fatigue states. For the high-dimensionality and multi-channel characteristics of the fNIRS signal data, a novel 1D revised CNN-ResNet network was proposed based on the double-layer channel attenuation residual block. The results showed a 97.78% accuracy in fatigue state classification, significantly superior than several conventional methods. Furthermore, a fatigue-arousal experiment was designed to explore the feasibility of forced arousal of fatigued subjects through exercise stimulation. The fNIRS results showed a significant increase in brain activity with the conduction of exercise. The proposed method serves as a reliable tool for the evaluation of fatigue states, potentially reducing fatigue-induced harms and risks.

Keywords fNIRS · Fatigue · Nap deprivation · Blood oxygen concentration · Deep learning

Introduction

Insufficient sleep-related fatigue is the cause of various harms physically and psychologically (Patrick et al. 2017 and Ishii et al. 2014). As a result, fatigue caused by sleep loss was related to increased incidents in transportation, aerospace, military, and other areas, leading to irreparable damage in these tasks, and posing a threat to human life and safety. While the impact of total sleep deprivation was likely to be more significant, sleep fragmentation or afternoon nap deprivation is much more often experienced in real-world contexts. Afternoon naps were shown to be positively related to cognitive health including memory and learning abilities (Leong et al. 2022). The deprivation of naps was shown to adversely affect cognitive functions, particularly alertness and response inhibition (Chen et al. 2018). Monitoring fatigue caused by nap deprivation is important in understanding the state of fatigue, alerting the operator to avoid accidents, and investigating fatigue-arousal methods.

Current research on cognitive fatigue due to sleep or nap deprivation primarily uses two methodologies. One involves the analysis of behavioral data from psychological experiments (Wylie et al. 2017), combined with self-assessment tools such as the Mental Fatigue Scale (MFS) (Johansson et al. 2010), the Fatigue Severity Scale (FSS) (Krupp et al. 1989), and the Visual Analog Scale for Fatigue (VAS-F) (Shahid et al. 2011). Riontino and Cavallero (2022) used the revised Attention Network Test (ANT-R) to identify specific effects of sleep deprivation on attentional network components during cognitive tasks. Liu and Zhang (2022) found that sleep-deprived subjects

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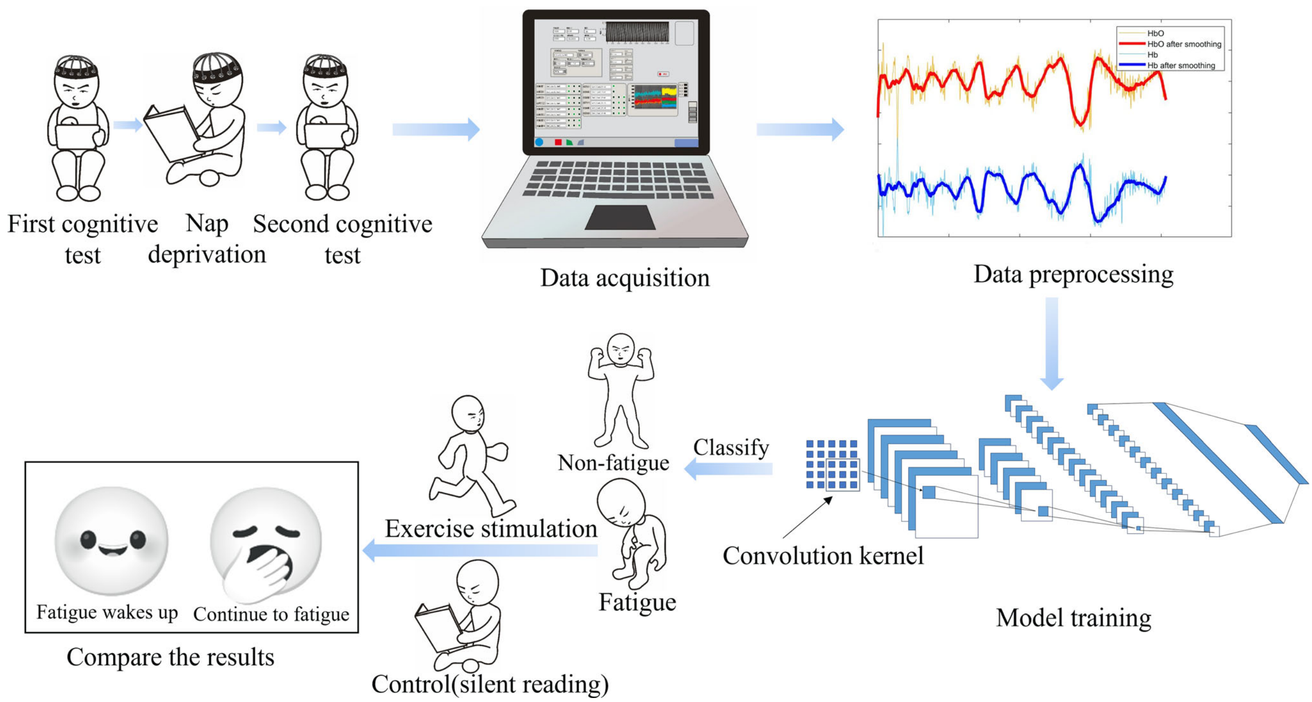

Fig. 1 Schematic diagram of the experiment

performing a Go/NoGo task exhibited longer reaction times and lower hit rates compared to controls. However, Mehta et al. (2017) noted limitations in subjective fatigue measures, finding no correlation between subjective scales and physiological indicators of fatigue in offshore shift workers. It indicated that conventional subjective methods may be inaccurate or not enough in determining the fatigue states.

The other methodology involves the recent use of physiological signal metrics as objective tools to assess the state of fatigue, such as electroencephalogram (EEG), electrocardiogram (ECG), and functional near-infrared spectroscopy (fNIRS) (Mohanavelu et al. 2017). These techniques offer potentially more accurate and intuitive assessments compared to psychological measures. EEG monitors brain electrical activity by detecting different rhythmic waves (α, β, θ, γ) based on frequency, providing insights into brain activation levels (Da Silva 2023). Despite its high temporal resolution (Li et al. 2022a, b), EEG is susceptible to motion artifacts and requires controlled experimental environments. ECG, through the analysis of heart rate variability (HRV), can detect cognitive fatigue; however, HRV can be influenced by individual differences, stress levels, and overall health status (Karim et al. 2024).

Compared to EEG and ECG, fNIRS has higher spatial resolution and is less affected by motion artifacts, physiological artifacts, and electromagnetism disturbance (Cao et al. 2022). fNIRS is a noninvasive, optical imaging technique that enables real-time monitoring of brain activation by measuring changes in cerebral blood oxygen levels (Li et al. 2022a, b; Kinder et al. 2022). During external task stimulation, neurovascular coupling induces an increase in oxygenated hemoglobin (HbO) and a decrease in deoxygenated hemoglobin (Hb), indicating brain activation. Conversely, during fatigue, these concentrations trend oppositely (Korhonen et al. 2013). Given the high absorption coefficients of HbO and Hb at 650–900 nm, fNIRS employs near-infrared light to detect these changes effectively (Gunasekara et al. 2022). Studies have demonstrated fNIRS's efficacy in monitoring fatigue (Varandas et al. 2022). Recently, machine learning algorithms have provided extra help in determining the brain fatigue. Pan et al. (2022) used fNIRS to monitor pilots' blood oxygen levels during flight missions and developed an SDAE model to recognize fatigue states, achieving 91.32% classification accuracy. Peng et al. (2022) combined fNIRS with genetic algorithms and a random forest (RF) model to classify fatigue levels, obtaining accuracies of 85.4% for fatigue vs. non-fatigue and 82.8% for moderate vs. severe fatigue. Zeng et al. (2021) integrated fNIRS data with facial feature analysis using MTCNN for image feature extraction and LSTM for fusion, achieving a fatigue prediction accuracy of 95.8%. Therefore, using fNIRS combined with machine learning or deep learning method is promising in the detection and understanding the brain fatigue states. Furthermore, these new tools can also contribute to the exploration of developing effective

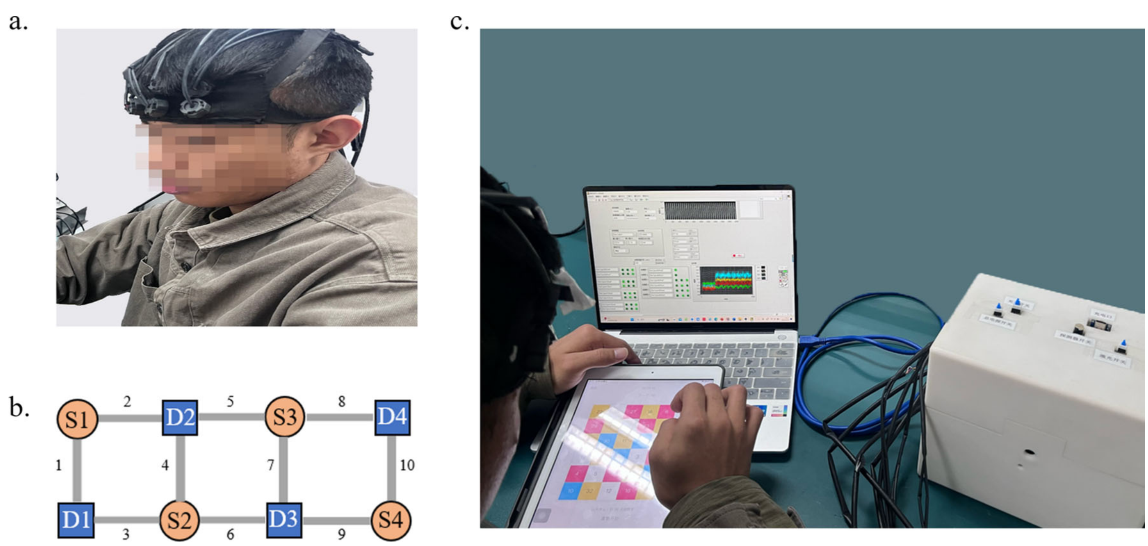

Fig. 2 fNIRS system diagram. **a**: the headband of the fNIRS system; **b**: channel distribution, where S represents light source, D represents detector, channels are formed between S and D, channel 6 covers the Fpz brain area and channel 5 covers the Fz brain area; c: the fNIRS system in experiments

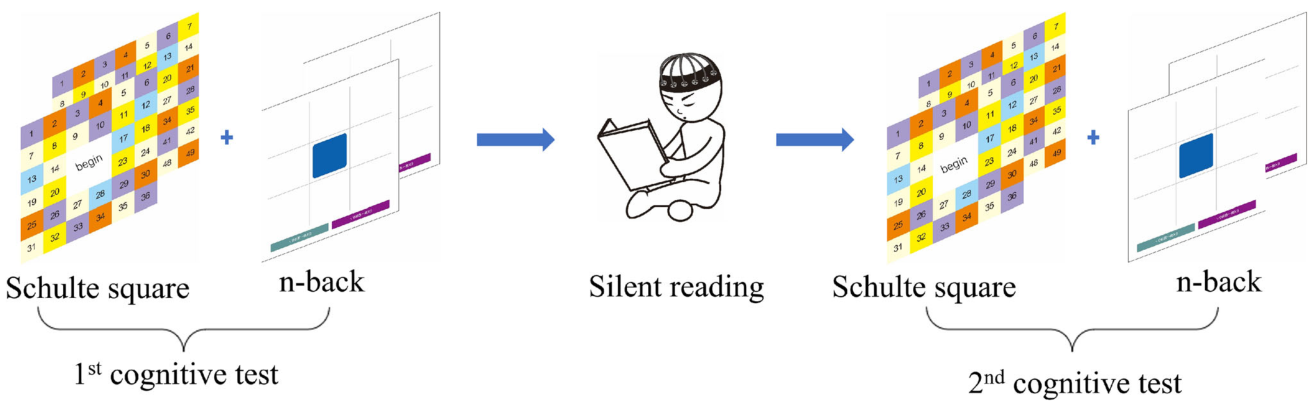

Fig. 3 Flowchart of the nap deprivation-induced fatigue experiment

fatigue-arousal methods in order to reduce the rish caused by fatigue.

Given the significant impact of sleep/nap deprivation on cognitive function and potential risks and the pressing need for reliable methods to be developed in monitoring and mitigating the effects of fatigue, we have focused on addressing the gaps in existing literature by developing a novel approach to monitor brain fatigue states caused by nap deprivation using fNIRS and deep learning. Utilizing a self-developed fNIRS system, we designed a series of experiments involving 18 participants who were deprived of their usual naps (Fig. 1). Both behavior data and fNIRS data were collected through the experiments and analyzed. We have also proposed an innovative 1D revised CNN-ResNet (1D-rCR) network model to classify fatigue states using fNIRS data, achieving a remarkable accuracy of 97.78%. Additionally, we explored the potential of exercise stimulation as a fatigue-arousal method, with the goal of providing a practical solution to reduce the risks associated with fatigue in operational settings. Our findings could contribute to the development of more accurate and reliable real-time fatigue monitoring systems and improve the design of effective interventions to enhance safety and performance in various situations.

Data acquisition

Participants

18 subjects were recruited for the nap deprivation-induced fatigue experiment, 10 males and 8 females, with a mean age of 25 ± 2 years old, healthy and no history of psychiatric disorders. All of the 18 subjects had a good napping habit. The studies involving human participants were reviewed and approved by Research Ethics Commission of

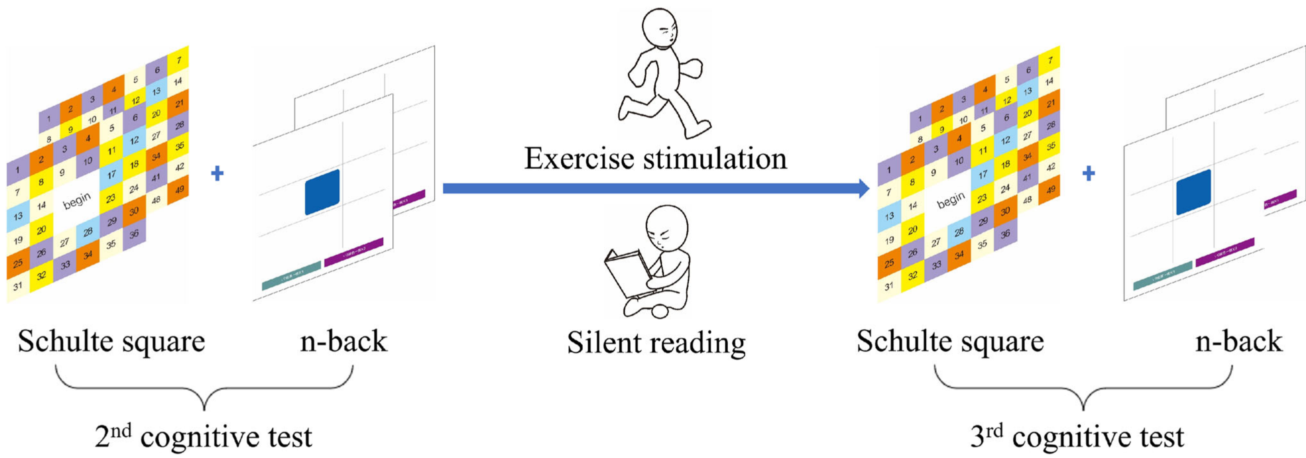

Fig. 4 Flowchart of the fatigue-arousal experiment

Naval Medical University. The patients/participants provided their written informed consent to participate in this study.

fNIRS system

The custom fNIRS system was composed of four pairs of light sources and four photodetectors, forming a total of 10 channels. Laser diodes (LDs) were used as light sources due to the narrow bandwidth of coherent light, greatly reducing the interference caused by the overlap of the wavelength of the light source. Each light source pair contained a 780 nm and a 850 nm N-type LD(QL78J6SA, QL85J6SA). Photodiodes (PD, TI, model OPT101) were used as photodetectors due to the low cost and acceptable performance, each was placed 3 cm apart from the light sources. All light source pairs and photodetectors were inserted on 3D printed adapters, which were embedded into a piece of spandex fabric to form a headband, ensuring tight contact with the skin as well as the comfort of the subject. The sampling rate of the detector was 5000 Hz. The headband was designed to be placed and make measurements on the prefrontal lobe. As shown in Figs. 2b S2 and D3 are located at the center of forehead, where channel 6 located at the Frontal poles zero (Fpz) location according to the standard International 10–10 system. The fNIRS device was shown in Fig. 2.

Experimental design

Nap deprivation-induced fatigue experiment

The experiment focuses on using fNIRS to monitor the fatigue status of the subjects when their naps were deprived. The experiment was conducted after lunch, a time point when the subjects normally took naps. Prior to the start of the experiment, subjects would fill out a Fatigue Scale (Nihashi et al. 2019) and then sit in meditation with their eyes closed for two minutes. Then the fNIRS data collection began. The experiment was divided into three phases (Fig. 3): a 20-min 1st cognitive test stage, a 40-min silent reading stage and a 20-min 2nd cognitive test stage. In both cognitive test stages, the subjects participated in two activities, the Schulte square game and an n-back test. The n-back consisted of two parts, the 1-back and the 2-back, when performing the 1-back task, the subject had to judge whether the color position of the nth square appearing in the screen is the same as that of the n-1th, and when performing the 2-back task, the subject has to judge whether the color position of the nth square is the same as that of the n-2nd. The silent reading stage served as the nap deprivation stage. The subjects were deprived of a nap, meanwhile they were required to engage in 40 min sedentary reading to prevent falling asleep or getting overexcited by other activities (Chen et al. 2018). Afterward, they completed the Fatigue Scale. The 2nd cognitive test stage served as the post-fatigue cognitive state, in which subjects completed the Fatigue Scale again and repeated the Schulte square game and an n-back experiment for 20 min.

Fatigue-arousal experiment

After the 2nd cognitive test, the 18 subjects continued to participate in a fatigue-arousal experiment. 10 subjects were in the fatigue-arousal group which performed exercise stimulation for 20 min (5 sets of squats), and the other 8 subjects continued to read silently during this time period. The fNIRS data was not acquired during this time period because of the system was not designed to be used on subjects with strong motion. Then, the subjects filled out another Fatigue Scale and performed a third cognitive test, so as to investigate whether the exercise stimulation has an effect on changing the fatigue state (Fig. 4). fNIRS data was acquired from the subjects when they were performing the 3rd cognitive test.

Methodology

Methods for analyzing cognitive test data

During the experiment, we gathered data on the duration participants spent playing the Schulte square game and their accuracy rates in the 2-back test. Prolonged game engagement periods and diminished test precision often serve as indicators for a state of fatigue in the subjects (Price et al. 2017). To assess the statistical significance of the observed differences, we employed Student's t-test using GraphPad Prism software. Furthermore, to ascertain whether the data obtained from distinct participants adhered to statistical assumptions, we conducted a two-way repeated measures the analysis of variance (ANOVA) using SPSS software (Borragán et al. 2019).

Methods for analyzing fNIRS data

Pre-processing

During fNIRS data acquisition, many types of noises existed, including electrical noise, experimental errors and physiological artifacts (Boas et al. 2004). Electrical noise often refers to the thermal noise of the instrument itself, which is mainly presented as a high-frequency signal and can therefore be filtered out by a 0.5 Hz low-pass filter. Experimental error mainly comes from the deflection of the subject's head during the experimental process, which leads to the bias of the fNIRS data acquisition, and is generally presented as an outlier in the data, which can be removed by threshold filtering. Physiological artifacts mainly contain heartbeat signal (1–1.5 Hz), respiratory signal (0.2–0.3 Hz), and Mayer wave (around 0.1 Hz), and a low-pass filter of < 0.1 Hz can remove most of the physiological signal noise (Paranawithana et al. 2022, 2023). Corresponding filters were applied on the raw data to remove the noises and artifacts. The light intensity data after preprocessing was converted into optical density, and the concentration change curves of HbO and Hb were obtained by using the modified Beer-Lambert law (MBL) equation (Asgher et al. 2019), which was given below.

$$\Delta OD = \left(\varepsilon_{HbO(\lambda)}\Delta C_{HbO} + \varepsilon_{Hb(\lambda)}\Delta C_{Hb}\right) \cdot DPF(\lambda) \cdot d \tag{1}$$

$$\begin{pmatrix} \Delta C_{HbO} \\ \Delta C_{Hb} \end{pmatrix} = \frac{1}{DPF \cdot d} \begin{pmatrix} \varepsilon_{HbO(\lambda_1)}\varepsilon_{Hb(\lambda_1)} \\ \varepsilon_{HbO(\lambda_2)}\varepsilon_{Hb(\lambda_2)} \end{pmatrix}^{-1} \begin{pmatrix} \Delta OD(\lambda_1) \\ \Delta OD(\lambda_2) \end{pmatrix} \tag{2}$$

where ΔOD is the optical attenuation, which can be calculated from the known incident light intensity and output light intensity measured; ε is the extinction coefficient; C is the concentration change of HbO and Hb to be solved; DPF

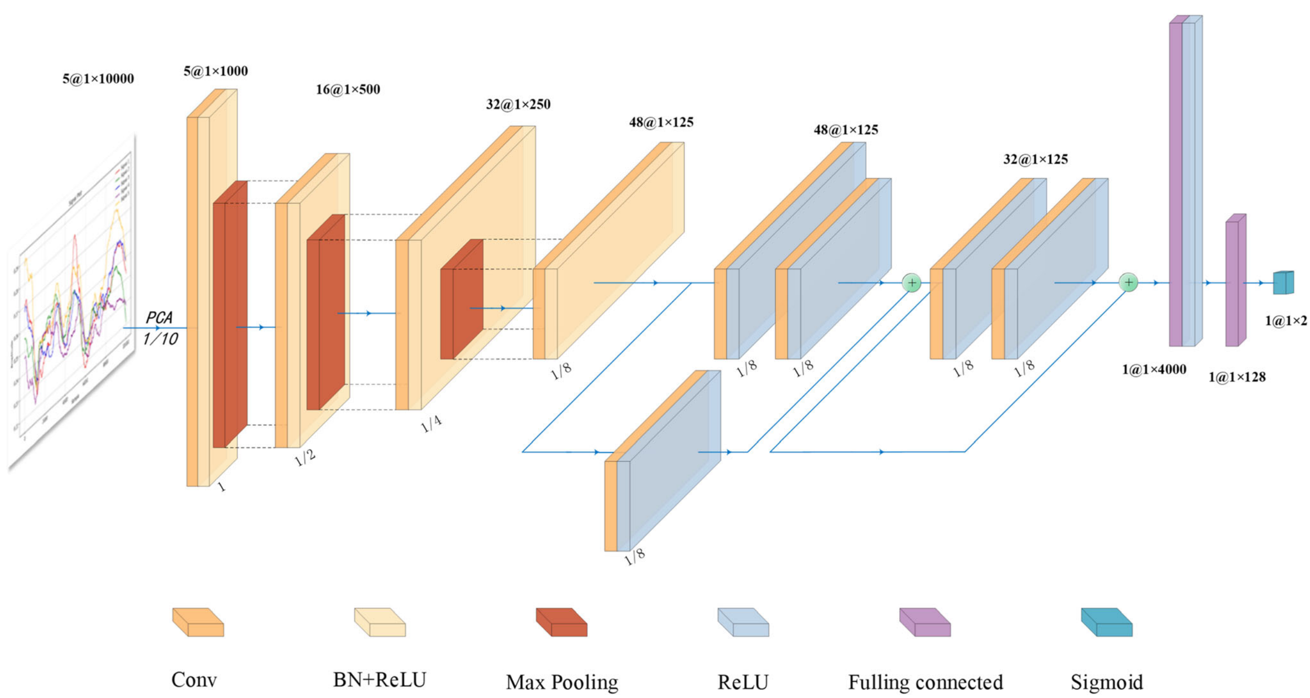

Fig. 5 1D CNN-ResNet network structure

Table 1 Hyperparameter of the proposed model

Hyperparameter	Value
Dimensionality reduction method	Principal component analysis (PCA)
Number of components	10,000
Optimizer	SGDM
Momentum	0.9
Activation function	ReLU
Loss function	BCELoss
Learning rate scheduler	CosineAnnealingLR
Initial learning rate	0.001
Cosine cycle	10
Minimum learning rate	0.0001
Epochs	100
Iteration per epochs	28
Batch size	8

is the differential path factor; d is the distance between the light source and the detector; and the wavelengths λ_1 and λ_2 of the two light sources were 780 nm and 850 nm, respectively.

Dataset

Ten channels of fNIRS data from the 18 subjects in the nap deprivation-induced fatigue experiment were acquired. Due to head movements and other factors, some channels exhibited noticeable drifts in the data for certain subjects.

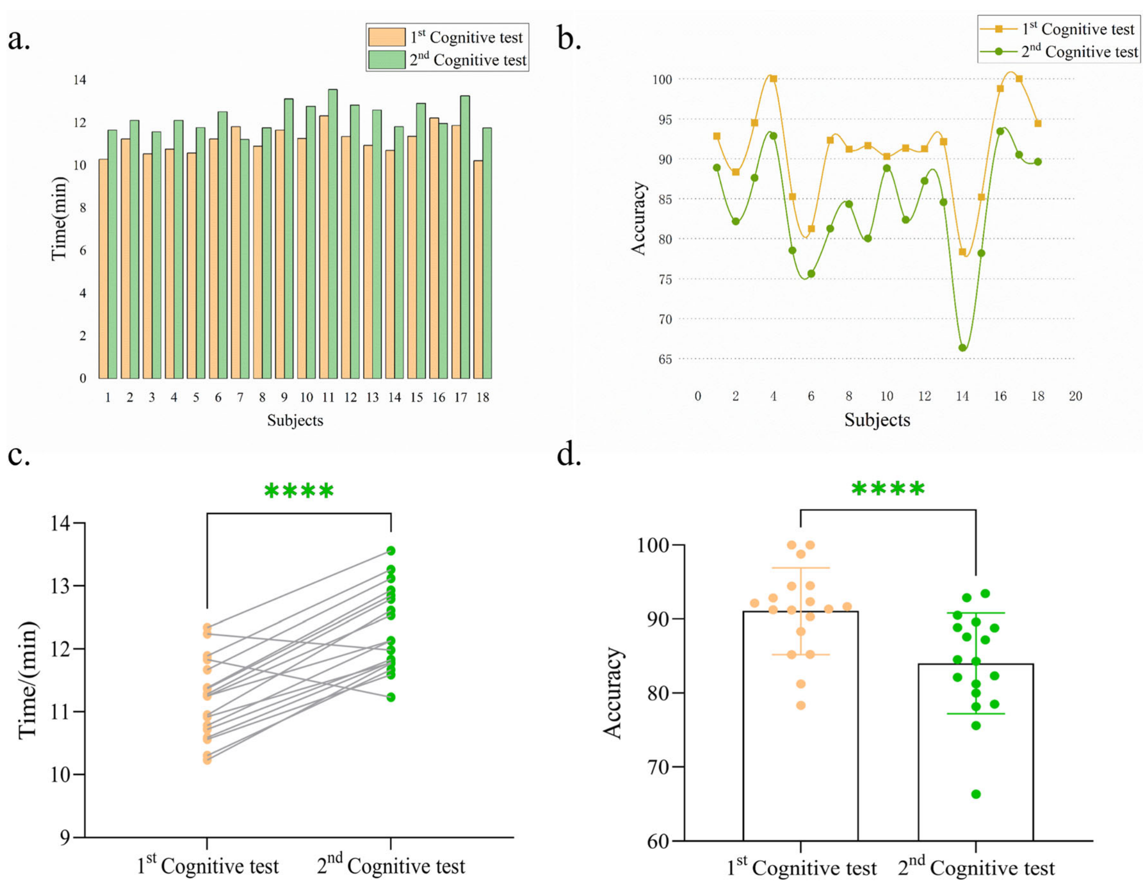

Fig. 6 Behavioral data analysis for the 1st and 2nd cognitive experiment. **a** Schulte square game duration comparison; **b** 2-back test accuracy comparison; **c** Schulte square game duration t-test results (****: $p < 0.0001$); **d** 2-back test accuracy t-test results (****: $p < 0.0001$)

Therefore, the data was thoroughly reviewed and five channels that were unaffected in all subjects were used for model training. The final retained channels covered brain regions including Fpz, Fz, AF1, AF2, Fp2, etc. After pre-processing, the fNIRS data yielded HbO curves. Data from each channel were cut into 5-min segments with a sliding time window (3 min apart). As a result, a total of 216 samples were obtained. During data acquisition, each detector acquired data from three channels (employed the method of time division multiplexing). Given a sampling rate of 5000 Hz, the data length corresponding to one sample per channel was 50,000 (5 * 60 * 5000 / 3). High sampling rates provide high precision but also introduce redundancy (Zeng et al. 2023). Therefore, to reduce data redundancy, an undersampling process with a sampling interval set to 0.01 s was performed, resulting in each segment size being 5*10,000. According to the Fatigue Scale, the signals collected in the first 20 min of the experiment (stage 1) were labelled as the non-fatigue state data, and the signals in the last 20 min (stage 3) were labelled as fatigue state data.

Model Architecture

In this paper, besides showing that the mental fatigue states can be observed with the cognitive test results and the fNIRS signals, we also proposed using deep learning on the fNIRS data to effectively classify mental fatigue states. This was achieved by developing a 1D revised CNN-ResNet model, which was described in detail below.

The 1D-rCR model is a network based on CNN and ResNet architecture, consisting of eight convolutional layers and two progressive residual blocks. The CNN structure can efficiently extract local features of the data. Through multi-layer stacking, the network can gradually build an abstract representation of the input data. The introduction of residual structure also includes convolution operations, which enhances the expression ability of the model, enables it to better fit the data distribution, and reduces the risk of overfitting.

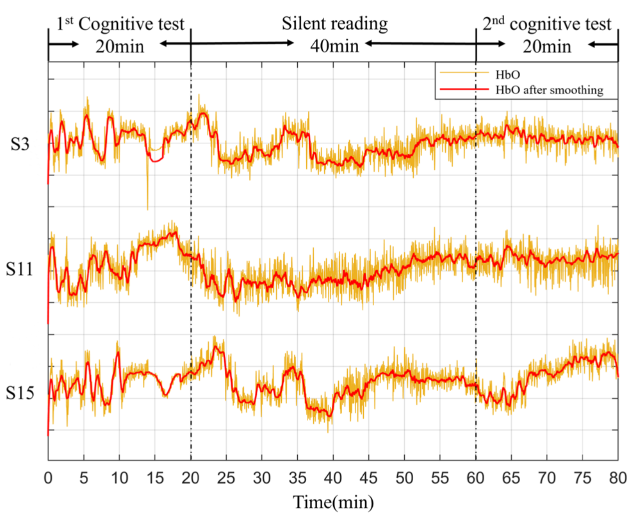

Fig. 7 HbO concentration profiles of three different subjects. S represents the subject, the y-axis indicates the relative changes in HbO concentration, yellow bars represent the original HbO concentration, and red bars represent the HbO concentration after regional smoothing

The proposed model architecture is illustrated in Fig. 5. Initially, principal component analysis (PCA) is employed for preliminary feature extraction to mitigate data redundancy. Subsequently, the data undergoes secondary feature extraction through four 1D convolutional layers, yielding a sampled representation. To enhance the model's efficiency in capturing discrepancies between input and output while alleviating overfitting, two residual structures are incorporated. We utilize the Rectified Linear Unit (ReLU) activation function to counteract gradient vanishing, and the Softmax function serves as the classification layer. The Binary Cross-Entropy Loss (BCELoss) function is selected as the loss function.

To ensure a more controllable learning rate, we combine Stochastic Gradient Descent with Momentum (SGDM) and a cosine annealing strategy for learning rate adjustment. Starting from an initial learning rate of 0.001, it is gradually reduced to 0.0001 via cosine annealing. Specific hyperparameters are detailed in Table 1.

Our dataset was partitioned into training and testing sets at an 8:2 ratio, specifically, data from 14 out of the 18 subjects were randomly selected as the training set, and data from the remaining 4 subjects were used as the test set, and we conducted a five-fold cross-validation. Performance was evaluated using precision, recall, accuracy, and F1 score, which were calculated according to the following formulas:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

$$F1 = \frac{2TP}{2TP + FP + FN} \quad (6)$$

where TP denotes true positive, FP denotes false positive, FN denotes false negative, and TN denotes true negative. This rigorous evaluation framework ensured that our model's performance was comprehensively assessed across various metrics, providing a robust validation of its effectiveness.

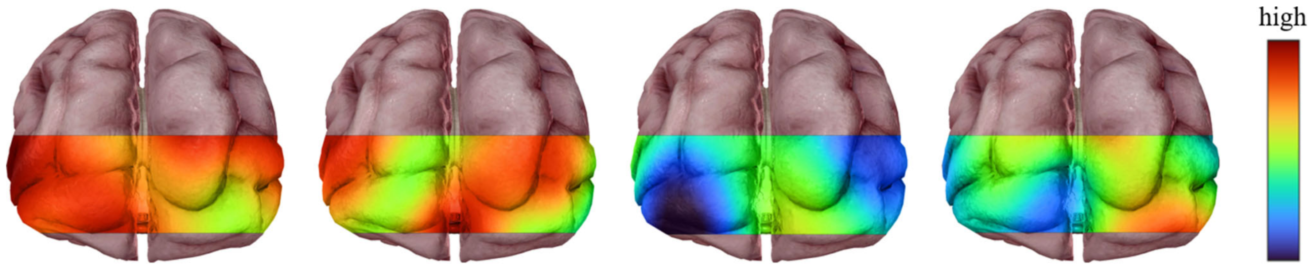

Fig. 8 Visualization of activation states in different regions of prefrontal cortex

Results and discussion

Nap deprivation-induced fatigue experiment

Behavioral data analysis

The behavioral data of the 1st and 2nd cognitive tests were analyzed and compared. In each cognitive test stage, the subjects performed the Schulte square game and an n-back test. The Schulte square game duration and the 2-back test accuracy were collected for analysis and the results were shown in Fig. 6. In the Schulte square game, it was evident that the majority of subjects took longer time to complete the test in the 2nd cognitive test compared to the 1st cognitive test. Similarly, in the 2-back experiment, the accuracy of subjects completing the 2-back test decreased significantly in the 2nd cognitive test. It was evident that the nap deprivation had successfully induce fatigue in the subjects. The data were subsequently analyzed statistically by analysis of variance (ANOVA). There was a significant difference in cognitive duration between pre-fatigue and post-fatigue (pre-fatigue M = 11.20 min, SD = 0.62; post-fatigue M = 12.31 min, SD = 0.66). Also, there was a significant difference in accuracy between pre-fatigue and post-fatigue (pre-fatigue M = 0.91, SD = 0.06; post-fatigue M = 0.84, and SD = 0.07). The *p*-value from the t-test indicates whether the difference between two groups is statistically significant. A *p*-value less than 0.05 suggests that we can reject the null hypothesis (which states that there is no difference between the two groups), meaning that there is a statistically significant difference between the two groups. The results of the t-test also indicated that there was a significant difference in the duration of the Schulte square game and the accuracy of the 2-back test between the pre-fatigue and post-fatigue conditions.

Analysis of fNIRS data

The fNIRS data was collected from all subjects during the entire experiment. Figure 7 showed the HbO concentration change from three representative subjects. According to the measurement principles of the fNIRS system, the HbO concentration we obtain is a relative change. Only HbO was shown because the concentrations of HbO and Hb basically show an opposite trend, according to the principle of neurovascular coupling. It can be seen that during the 1st cognitive test, the subjects' HbO profiles fluctuated markedly, representing that the brain was in an active state at this point. At the end of the 1st cognitive test, the subjects were nap deprived and entered the silent reading stage. As can be seen in the figure, the subjects' HbO concentration showed a decreasing trend, and then the subjects gradually entered a fatigue state, with the HbO changing slowly and gently, indicating the decrease of brain activity. It is worth noticing that when the HbO concentration decreased to a certain extent, instead of decreasing even further, it started to gradually increase. This is because the human oxygenation system will respond to force an increase in the HbO level to ensure the normal function of the brain (Masamoto and Tanishita 2009)). This phenomenon was confirmed in this experiment, as shown in the curves at the end of silent reading (40–50 min). Subsequently, the

Table 2 Model performance comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Rf	89.71	89.99	89.71	89.76
LSTM	86.67	90.48	82.61	86.36
Bi-LSTM	88.89	87.50	91.30	89.36
RNN	80.00	79.17	82.61	80.85
CNN	93.33	91.67	95.65	93.62
1D-rCR	97.78	96.00	100	97.96

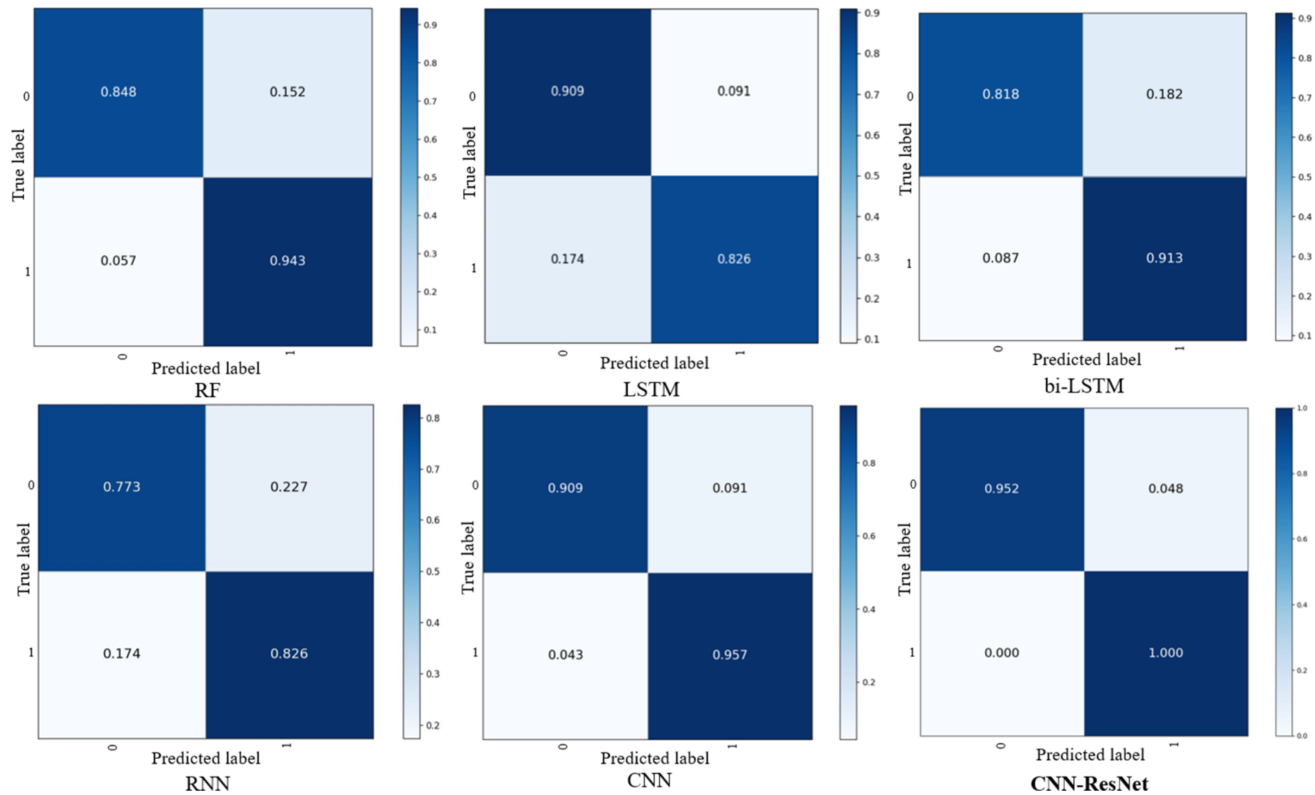

Fig. 9 Confusion matrices for six classifiers

subjects entered the 2nd cognitive test, repeating the Schulte square game and the n-back tests. From the analysis in 4.1.1, it can be concluded that the subjects were in a fatigue state during this time period, and it can be seen that the HbO curves were much smoother than the beginning 20 min. This matched the analysis of the Fatigue Scale and the cognitive data that the sleep-deprivation had successfully induced mental fatigue.

The five-channel HbO data were also shown in heatmap to indicate the fatigue state change of the subjects. Using subject 15 as an example, the blood oxygen concentration in different regions of the prefrontal lobes of the brain was mapped at several time points (Fig. 8). Red color represents high concentration of HbO while blue represents low concentration of HbO. We can see that during the subject's 1st cognitive test, the heatmap was dominantly red, indicating a high HbO level and an active state of the brain. As the 1st cognitive test ended and the subject entered the silent reading period, the brain was still activated, but with a decrease in HbO concentration compared to the previous map. In the later stage of silent reading, the subject began to be in a state of fatigue, and the blood oxygen concentrations were at their lowest levels at this time. When the reading ended and the subject took the 2nd cognitive test, the blood oxygen concentration slightly increased due to the stimulation of the cognitive test, but it was still at a lower level compared to 9th min and 29th min, showing that the subject was still in a certain fatigue state. This observation was consistent with the trend of the HbO curves and the cognitive data analysis.

Fatigue state classification based on 1D revised CNN-ResNet model

This study aimed to use fNIRS as an objective physiological measurement-based approach for classifying fatigue states. A 1D revised CNN-ResNet (1D-rCR) model was developed to improve the convenience and accuracy of fatigue state identification. Our model was trained using the fNIRS dataset collected through nap deprivation experiments in 2.3.1.

A comparative evaluation against other machine learning and deep learning methods was conducted, with the classification outcomes of fatigue versus non-fatigue conditions assessed using the quartet of metrics detailed in 3.2.3. The findings, presented in Table 2 and Fig. 9, revealed that Random Forest (RF) surpasses recurrent neural network architectures, including RNNs, across several performance indicators. We attributed this observation partly to RNNs' suboptimal handling of exceedingly lengthy sequential data. Notably, our proposed model, which integrated a residual structure, achieved a 4.45%

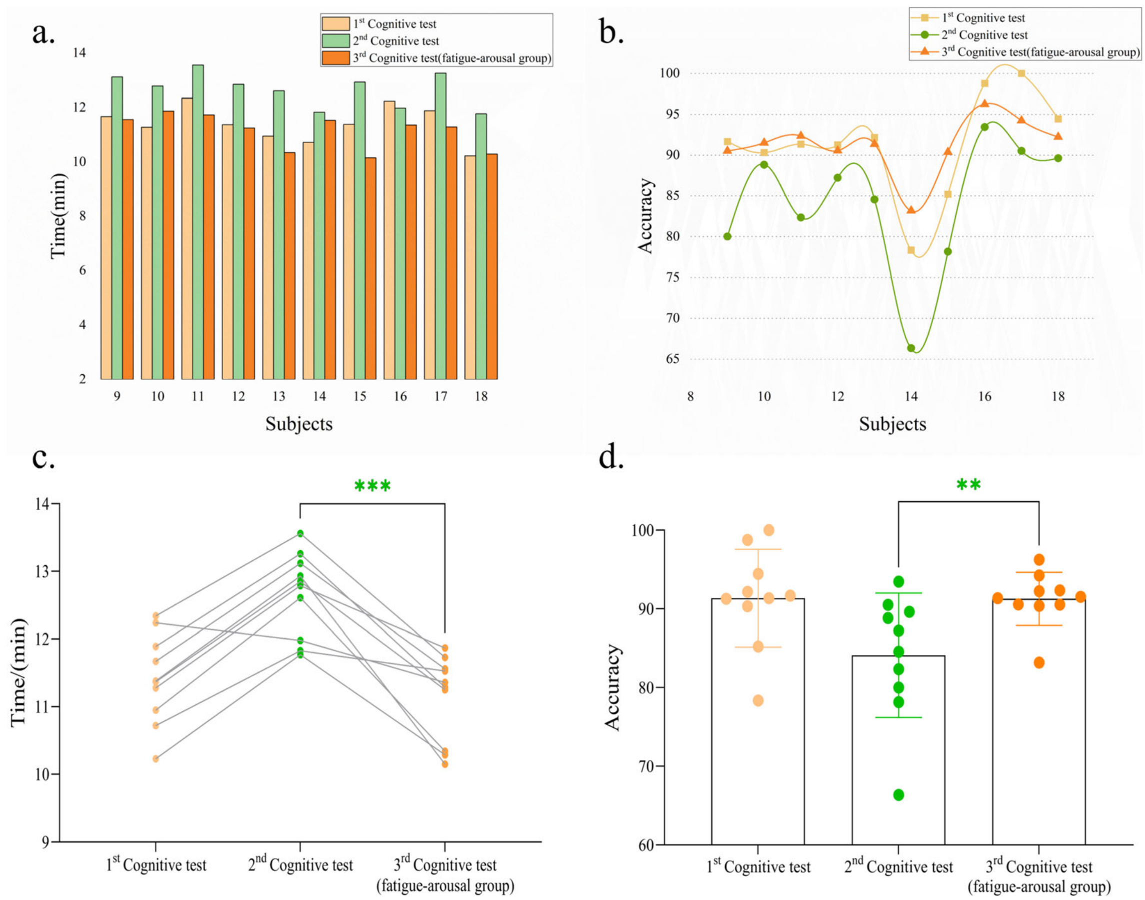

Fig. 10 Results of the 1st, 2nd, and 3rd cognitive tests for the fatigue-arousal group **a** Schulte square game duration comparison; **b** 2-back test accuracy comparison; **c**Schulte square game duration T-test results (***: $p < 0.001$); **d** 2-back test accuracy T-test results (**: $p < 0.01$)

increase in classification accuracy relative to a standard CNN. Furthermore, it excelled across all evaluation metrics when juxtaposed with alternative models, highlighting its efficacy and robustness in fatigue state classification tasks.

Results and discussion of fatigue-arousal experiment

Behavioral data analysis

To evaluate the effectiveness of the fatigue-arousal method (exercise stimulation), the results of all three cognitive tests were analyzed. Specifically, the Schulte square game cognitive duration and 2-back accuracy were collected. The 1st cognitive test was performed before the nap deprivation period, and previous results showed that the brain was active at this point, therefore the stage was defined as a pre-fatigue state. The 2nd cognitive test was performed after the fatigue inducing period, and previous results showed that the subjects were in a mental fatigue state, therefore the stage was defined as a post-fatigue state. Then, 10 subjects participated in exercises, therefore were defined as the fatigue-arousal group, while the other 8 subjects continued to performing reading tasks and were defined as the persistent fatigue control group.

Figures 10 and 11 illustrated the results of cognitive performance assessments in two distinct scenarios. Panel (a) depicts the changes in subjects' performance in the Schulte square Game and their accuracy in the 2-back test, both pre- and post-exercise stimulation. Notably, following exercise intervention, participants demonstrated a reduction in the time required to complete the Schulte square game and a concurrent increase in accuracy on the 2-back task. Conversely, the control group, who continued with silent reading, exhibited an increase in the time taken to finish the tests, with no substantial improvement in accuracy.

To further validate these observations, statistical analyses were conducted using SPSS software. The analysis revealed a statistically significant difference between the

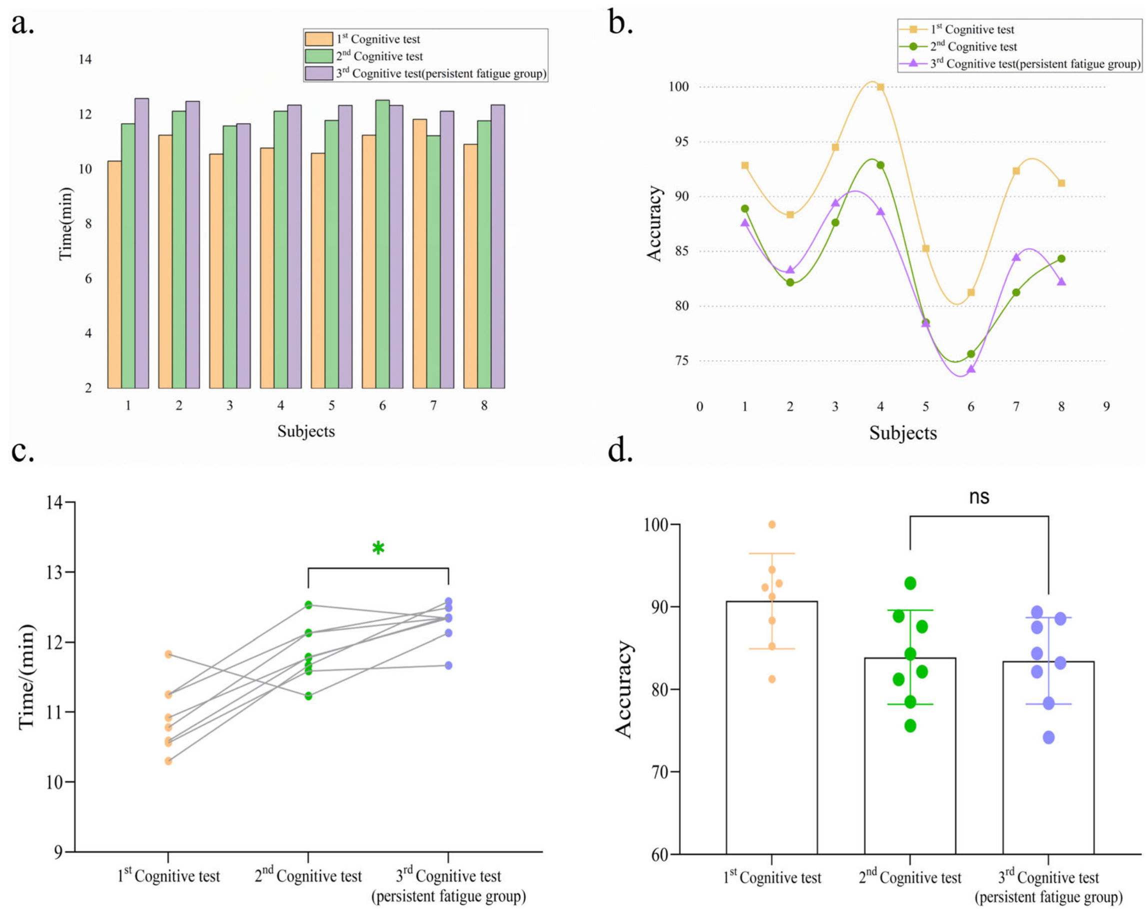

Fig. 11 Results of the 1st, 2nd, and 3rd cognitive tests for the persistent fatigue group **a** Schulte square game duration comparison; **b** 2-back test accuracy comparison; **c** Schulte square game duration T-test results (*: $p < 0.05$); **d** 2-back test accuracy T-test results (ns (not significant): $p > 0.05$)

Schulte square game durations when comparing post-fatigue (M = 12.67 min, SD = 0.62) to post-exercise stimulation (M = 11.14 min, SD = 0.64). Similarly, a significant difference was observed in 2-back accuracy levels, with post-fatigue scores averaging at M = 0.84, SD = 0.08, compared to M = 0.92, SD = 0.04 following exercise stimulation. Regarding the control group that maintained the silent reading activity, no statistical difference was noted in either the Schulte square game duration (fatigue: M = 11.86 min, SD = 0.40; silent reading: M = 12.28 min, SD = 0.28) or accuracy rates (fatigue: M = 0.84, SD = 0.06; silent reading: M = 0.83, SD = 0.05) when compared to the post-fatigue group. The t-test results showed a significant difference in the duration of the Schulte square game and the accuracy of the 2-back test between the post-fatigue and the fatigue-arousal group. This suggested that physical exercise to helped the participants recover from fatigue. For the post-fatigue and the persistent fatigue control group, there was a statistical difference in the duration of the Schulte square game, which was attributed to an increase in the average duration. This indicated that a greater fatigue state was resulted from the extended reading time. There was no significant difference in 2-back accuracy between the two groups, indicating that the participants did not recover from their fatigued state. Collectively, these findings robustly indicated that exercise stimulation can serve as an efficacious means to revive cognitive function from a fatigued state, thereby endorsing its potential as a cognitive rejuvenation strategy.

Analysis of fNIRS data

Figure 12 presented fNIRS HbO data from two representative subjects throughout the fatigue-inducing and fatigue-arousal experiments. In the fatigue-arousal experiment, subject 3 (S3) was the reading control while subject 11 (S11) participated in the exercise stimulation. After the 40-min silent reading stage, both subjects showed significant decrease in their brain activity, a sign of entering the

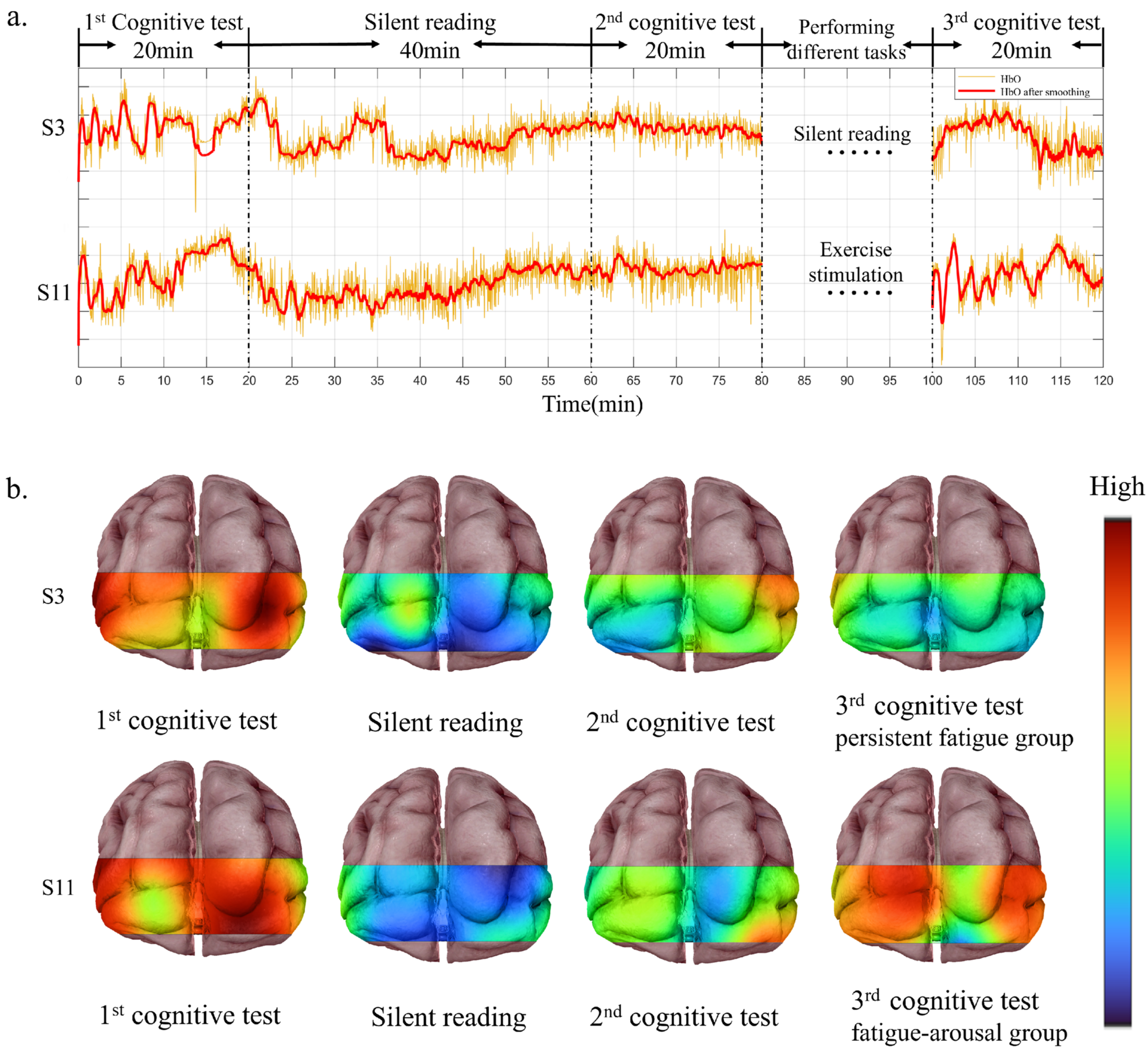

Fig. 12 Visualization of HbO concentration and brain activation throughout the experiment for two subjects. **a** HbO concentration changes for subject 3 (S3) and subject 11 (S11). Yellow bars represent the original HbO concentration, and red bars represent the HbO concentration after regional smoothing. **b** Heatmaps of prefrontal activation level. S3: the control group; S11: the exercise-stimulation group

fatigue state. The lack of activity continued when the subjects performed the 2nd cognitive test. The results of 2nd cognitive test highly matched the results of the fNIRS data. After performing different tasks in the fatigue-arousal experiment, S11 showed increases in HbO concentration and significantly increased activity levels while S3 did not show much changes from the calm state. The heatmaps of the prefrontal cortex of the two subjects in Fig. 12b showed the same trend. This indicated that exercise may be an effective stimulation to arouse the fatigue state for people in sleep-derivation induced fatigue state.

Conclusion

In this paper, we have proposed using fNIRS to study and analyze the state of brain fatigue caused by nap deprivation. A custom-built fNIRS system was placed at the prefrontal cortex and keep recording during the sleep-deprivation period and the cognitive paradigms. The cognitive paradigm was composed of a Schulte square game and a 2-back test as the cognitive evaluation of the fatigue states and was performed at several time points. The fNIRS data from 18 subjects was used to extract HbO waveforms and heat maps, which served as physiological indicators for fatigue states. The fNIRS data was also input into a proposed 1D-rCR model to classify the fatigue states. The classification accuracy reached 97.78%, outperformed several other popular models. Finally, an exercise stimulation experiment was designed as a fatigue-arousal method, and was demonstrated to be effective with the evaluation using fNIRS and the cognitive paradigm. As was shown in this paper, fNIRS served as an objective physiological tool for the analysis of mental fatigueless, and can be a complement of cognitive evaluations and vice versa. Especially, deep learning algorithms can be used in the analysis of fNIRS data, further improving the accuracy of fatigue state evaluation. In the future, the number of fNIRS channels can continue to be expanded, and the fatigue states can be better defined, to facilitate high-precision measurements of the entire brain in more complicated situations. This is of great importance to applications in transportation, aerospace, military, etc.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interests The authors declare no competing interests.

Ethical approval This paper involved human participants, and it is confirmed that all participants provided informed consent in accordance with the relevant guidelines.

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